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Technology-enabled business models and the consequences on tourism industry:
current impacts on incumbents and communities and future impacts from AI technology adoption

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Declaration

I hereby declare that, the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

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I would like to dedicate this thesis to whoever makes me grow

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Abstract

Since early 2000s it is possible to witness to the relentless rise of **electronic platform-based companies** in almost every industry. The development of a technological infrastructure able to easily transfer and store even more data made possible the rapid diffusion of internet networks in most countries. The availability of cheap internet connections in most of our houses and mobile devices allowed and contributed to the creation of innovative business models able to exploit the great value hidden there. Usually this context has led to the rise of few champions in each industry able to dominate the digital channels of the market. This mechanism follows the “winner takes it all” logic, where the first companies able to reach the critical mass level of users get a position almost unreachable for the followers, due to the higher value offered to new users thanks to the network effect and the bandwagon effect. The **consequences of these champions’ rise on the society** are one of the most interesting socio-economics phenomena of our times. Successful digital-native companies have been able to exploit the power of the information in order to scale extremely fast, often overcoming incumbents in many economic and financial key performance indicators. Because of the timeliness of the phenomenon literature is still dealing with the subject and there are many gaps to be filled. Transportation, finance, tourism are all industries undergoing a process of change of internal and external equilibria due to the entrance of digital platforms in their markets, usually able to work more efficiently thanks to a lighter cost structure, possible because they were born as digital companies. The objective of this thesis is to estimate the current socio-economic consequences of the past

diffusion of electronic platforms and to observe and postulate about the future consequences coming from the diffusion of the artificial intelligence technology, that is happening nowadays.

Using tourism industry and accommodation sector as setting of the research, this thesis applies multiple quantitative methods to test managerial theories extracting knowledge from two proprietary datasets, one related to all Airbnb listings in Italy and the other one related to all European artificial intelligence start-ups related to tourism. Adopting a deductive research approach, the thesis work started analysing the literature available about the managerial theories illustrating the challenges and opportunities of companies facing technology-enabled business model evolution, in order to test their validity in the specific circumstances given by the chosen research setting. To investigate the consequences of electronic platform business model diffusion some fixed-effect panel regression models have been run keeping as independent variable Airbnb diffusion and varying dependent variables and moderators. Furthermore, some analyses have been performed on successful artificial intelligence start-ups operating in the industry to postulate regarding the future consequences of current diffusion of artificial intelligence technology based business models.

In this vein, one of the debated points in literature is whether these new-born champions are building their success enlarging the market to new customers or stealing market shares to the incumbents, and how incumbents should react to the threat, if any. This thesis analysed the impact of Airbnb diffusion on hotels' profitability in the specific setting of Italian main touristic cities, finding that some categories of hotels suffer more than others.

Incumbents may be the first actors noticing the consequences of the rise of new business models, but on the other hand it is also interesting to explore how touristic destinations perceive this changes. In this regards the thesis analysed the consequences of Airbnb diffusion on rural Italian touristic destinations, finding that it could behave as an economic flywheel, increasing the wealth of these destinations.

Finally, the thesis shows the current trends related to the adoption of artificial intelligence happening in tourism industry. Applying text analytics to categorize all European artificial intelligence start-ups dealing with tourism industry and measuring their success it is possible to postulate how the tourism industry will change in the next years.

Overall the results point out how successful digital native electronic platforms are having a deep impact on the whole touristic ecosystem, contributing to induce changes we are all able to witness in our lives. These changes will be further enhanced by the adoption of artificial intelligence.

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Chapter 1

Introduction

1.1 Background

Tourism industry is one of the largest and most complex economic sectors existing nowadays, with increasing number of travellers worldwide and huge changes ongoing due to many factors. Technological evolution, social changes in both developed and development countries, COVID-19 pandemic are some of these factors increasing uncertainty about the future and all the entities in the industry are witnessing the changes involved by them. The resulting ambiguity calls for answers to the emerging challenges and in order to provide with answers it is necessary a better understanding of the mechanisms ruling these changes.

Technological improvement is one of the major forces reshaping the industry, since it defines what is technically feasible for the actors in the industry, de facto making possible the digital transformation process impacting so strong in so many industries (Kraus, Palmer, Kailer, Kallinger, & Spitzer, 2019; Nambisan, Wright, & Feldman, 2019). Great part of these changes happens because people like the entrepreneurs and innovators look for new ways to combine these new technology improvements in order to offer new value propositions and the companies have to adapt in order to survive (Chalmers, MacKenzie, & Carter, 2020; Nambisan, 2016; Zaheer, Breyer, & Dumay, 2019). Investing in digital transformation has become necessary for every company, since it allows to improve business processes and experiment new ones (Zaheer et al., 2019). In this process usually there is a fight between the old habits and the change both inside companies and among companies. This is a well-known phenomenon many researchers studied and proposed frameworks to explain, like Porter's five forces (Porter, 1979), Resource Based View (J. Barney, 1991; Wernerfelt, 1984) and Disruptive innovation (Christensen, 1997) to cite some of them. The technologies upon which these new business models are built are called general purpose technologies, and are defined with this name because they are a general tool that allows advancement for society and economy (Bekar, Carlaw, & Lipsey, 2018).

Notwithstanding the great amount of effort past researchers dedicated to the subject there are still many important questions to reason and discuss about. What are external or internal characteristics of company able to defend profitability in this evolving environment? What are the characteristics of the entities that could benefit from the diffusion of innovative general purpose technologies? What are the future trends in terms of industry structure evolution? This thesis aims at answering to some of these questions measuring the current impacts of past advancement in information and communication technologies and estimating the future consequences of current diffusion of artificial intelligence in some specific settings belonging to the tourism industry.

One of the main business models made possible by information and communication technology evolution is the digital platform. Digital platforms create value connecting demand and supply of a good, and scale very rapidly once reached the critical mass, following the winner-takes-it-all logic, since the value for each user grows with the growth of the user number (Constantinides, Henfridsson, & Parker, 2018; Evans & Schmalensee, 2016). Accommodation and hospitality sector is one of the sectors that are being revolutionized the most by these platforms, given the entrance of huge game changers like Booking.com, Tripadvisor and Airbnb (Frenken & Schor, 2017; Hamari, Sjöklint, & Ukkonen, 2015; Marios Sotiriadis, 2017; I. P. Tussyadiah & Pesonen, 2016). One of the countries where this revolution is more evident is Italy. Italy is one of the most visited countries in the world, and accommodation and hospitality sector here is a vital component of the economy, even if characterized by a very fragmented structure of the offer. In accommodation and hospitality sector the main consequences impact on the incumbents and on the communities where the digital platforms spread. These two will be the main areas of focus of the first part of thesis.

General purpose technologies are defined as fundamental source for further general purpose technologies (Bekar et al., 2018). One of the main evolutions of information and communication technology is the artificial intelligence (Taddy, 2018). As information and communication technology also artificial intelligence is impacting and will impact in the near future the competitive structure of industries like tourism enabling new business models, yet current literature has just started wondering what could be these changes and how they will be happening in near future. For these reasons, this thesis aims at estimating the future structural changes in tourism industry analysing what are the start-ups winning the trust of the market, the characteristics of their founders, the services they offer and which kind of customers they target. Start-ups in the scope of this thesis are considered as a fundamental way to validate and foster innovation from research to market.

It is clear innovation does not come without consequences towards existing equilibria, yet, in tourism and hospitality markets there are still big gaps to be filled regarding the context and the characteristics that may be moderating this relationship and the future evolution of these equilibria. The thesis aims at filling these gaps contributing to shed light in the future choices of mangers and policy-makers, other than paving the way for future researchers of this fascinating and complex industry.

1.2 Research questions

Tourism industry, as many others, is an omnipresent, multifaceted & dynamic industry undergoing a process of rapid evolution due to technological innovation (Frenken & Schor, 2017; Hamari et al., 2015; Marios Sotiriadis, 2017; I. P. Tussyadiah & Pesonen, 2016). Information and Communication Technology particularly has reshaped and it is still reshaping the way companies interact with the customers and among each other (Bethapudi, 2013; Gretzel, Sigala, Xiang, & Koo, 2015; S. G. Lee, Trimi, & Kim, 2013), and yet we can expect further changes due to the diffusion of Artificial Intelligence based business models (Crafts, 2021; Murphy, Hofacker, & Gretzel, 2017; Tsaih & Hsu, 2018). However, being clear something is changing, current literature still has many gaps to be filled when considering specific situations, and this thesis aims at filling some of them.

Generally speaking, the primary target of the thesis is *to examine how General Purpose Technology enabled innovative business models impact on competitive equilibria among companies and destinations in the hospitality market and in the tourism industry*. The thesis captures the impact of these innovative business models in different contexts, highlighting moderation variables that influence the direct relationship. Given the huge size and the intrinsic differences existing in tourism industry the thesis could not and does not want to take into consideration and deepen each single possible impact coming from technological improvement to the tourism industry, but at the same time it is able to answer different questions about those abovementioned impacts.

The first part of the thesis aims at examining the consequences happening nowadays due to the massive diffusion of digital sharing economy platforms in hospitality sector. Information and Communication Technology has made possible the rise of digital sharing economy platforms, making effective the matchmaking mechanism between underutilized goods supplier and those seeking for them, and also altering the competition dynamics between incumbents and new entrants (Zeng, Mahdi Tavalaei, & Khan, 2021). Airbnb is the most successful and representative accommodation digital platform, at least in western countries and in Italy, with more than 6 million accommodation listings from 192 countries (Airbnb, 2019), and its diffusion is impacting both the traditional hospitality providers, and the entire society (Hansen Henten & Maria Windekilde, 2016). Past literature has already demonstrated that in general Airbnb acts as a substitute to hotels, stealing market share to this kind of incumbents in a significant way, given its large diffusion (Akbar & Tracogna, 2018; Forgacs & Dimanche, 2016; Guttentag, 2015; Zervas, Proserpio, & Byers, 2017). The first objective of this thesis is exploring moderation variables that could influence of not this relationship in an environment where tourism is an established factor, so the first research question reads as follows:

RQ1. To what extent can the rent positions, due to the attractiveness of a hotel's position and its online reputation arising from its ordinary capabilities, influence the impact of the diffusion of short-term rental sharing-economy solutions on independent hotels at a city level?

The first moderator we took into consideration is the location of the hotel in an attractive city zone or not, a factor able to influence the travelers choices in accommodation selection that can be considered as a Ricardian rent (Kivell, 1993; Montgomery & Wernerfelt, 1988; Prieto-Rodriguez & Gonzalez-Díaz, 2008). The second moderator is the online reputation of a hotel, a proxy of the capability of hotels to manage daily business by the eyes of its customers that all prospect can see online (Paiva & Vasconcelos, 2019).

But, if on one hand, in destinations already popular Airbnb may represent added competition to the incumbents, on the other hand the lesser known destinations may benefit from sharing economy accommodation platforms when looking for sources of income and avoiding depopulation (Battino & Lampreu, 2019; Strømmen-Bakhtiar, Vinogradov, Kvarum, & Antonsen, 2020; I. P. Tussyadiah & Pesonen, 2016). Rural tourism may be a mean to improve local economy and to create jobs in rural communities (Pröbstl-Haider, 2010; Pröbstl-Haider, Melzer, & Jiricka, 2014), so the second research question reads as follows:

RQ2: Under which circumstances, can sharing economy accommodation platforms act as an economic flywheel for rural touristic destinations?

In the second part of the thesis the focus shifts from analyzing the current consequences of Information and Communication Technology diffusion, happened many years ago, to exploring the future possible consequences of Artificial Intelligence, a general purpose technology that is developing and spreading in present time, expanding the focus of observation to the entire tourism industry. Since Artificial Intelligence is considered by many as a trigger to a new digital transformation (Murphy et al., 2017), able to evolve structures, routines and the way companies generate value (K. Xie, Wu, Xiao, & Hu, 2016), we expect that will affect consumer behavior and impact on the industry structure in the near future. The thesis aims at estimating the effects of this current revolution analyzing what are currently doing the most promising startups of the sector, since start-ups are considered the main way through which established companies are exposed to innovations (Groen, Wakkee, & De Weerd-Nederhof, 2008; Markides, 2006; Walsh, 2004). Since it deals with future consequences of current phenomena, this second part of the thesis cannot support any hypotheses and do not state any of them; on the contrary it is composed by a set of more specific research questions:

RQ3: What are the characteristics of VC-backed tourism AI start-ups?

RQ4: What are the VC-backed AI start-ups technological domains?

RQ5: What is/are the phase/s of the tourism supply chain where AI start-ups received the highest amount of funding from VCs?

The three research questions aim at guessing how tourism industry will change by looking at the common characteristics of the successful start-ups. It is expected that the start-ups able to convince the market to invest will be the one shaping the future of the industry, so it is reasonable to assume that the category of start-ups with more investments will be the ones with higher impact on the phases of supply chain involved. Table 1 summarize the research questions.

Table 1: Research questions and hypothesis

Research questions	Hypothesis/specific research questions
To what extent can the rent positions, due to the attractiveness of a hotel's position and its online reputation arising from its ordinary capabilities, influence the impact of the diffusion of short-term rental sharing-economy solutions on independent hotels at a city level?	*The attractiveness of the city zone where a hotel is located positively moderates the effect that the diffusion of home-sharing platforms has at the city level on the hotel's profitability growth, with hotels located outside the most attractive zones suffering the most* *The online reputation of a hotel positively moderates the effect that the diffusion of home-sharing platforms has at the city level on the hotel's profitability growth, with lower online reputation hotels suffering the most*
Can sharing economy accommodation platforms act as an economic flywheel for rural touristic destination?	*Airbnb supply increases the touristic flows of the rural destination* *Online visibility, measured by the presence of destination's institutional and touristic websites, positively moderates the relation between Airbnb supply and the touristic flows of the rural destination*
What is the current status of development of European tourism AI start-ups and what direction is taking?	*What are the characteristics of VC-backed tourism AI start-ups?* *What are the VC-backed AI start-ups technological domains?* *What is/are the phase/s of the tourism supply chain where AI start-ups received the highest amount of funding from VCs?*

1.3 Framework of analysis

1.3.1 Main concepts

General Purpose Technology (GPT) can be defined as a "single technology, or closely related group of technologies, that has many uses/is widely used across most of the economy, is technologically dynamic in the sense that it evolves in efficiency and range of use in its own right, and is complementary with many downstream sectors where those uses enable a cascade of further inventions and innovations" (Bekar et al., 2018). Electricity, steam engine, internal combustion engine and ICT are among the most well-known examples of GPT, given their importance and impact in socio-economic activities (Jovanovic & Rousseau, 2005). All these technologies have deep impacts on the way companies produce and population consumes. Usually GPTs destabilize the competitive environment eliminating or eroding the sources of comparative advantage for an industry while generating possibilities for new companies to enter in it (Klinger, Mateos-Garcia, & Stathoulopoulos, 2018). Past literature has listed six fundamental characteristics to identify a GPT, reported hereunder (Bekar et al., 2018; Bresnahan & Trajtenberg, 1995). First, "Complementarities with a cluster of technologies that define and support it"; the evolution of each sub-component of a GPT is complementary towards the other sub-components part of the same cluster of technologies defining the GPT (Bekar et al., 2018). Second, "Complementarities with a cluster of technologies that it enables"; the evolution of each sub-component of a GPT is complementary towards the innovation process happening downstream. In other words GPT have a role of technological enablers (Bresnahan & Trajtenberg, 1995) since often downstream innovation would be economically or technically not possible (Bekar et al., 2018). Third, "Complementarities with a cluster of technologies that typically include those that are socially, politically and economically transformative"; adoption of GPT is widespread among the applications having an impact on socio-economic structure and these application deeply modify this socio-economic structure, pushing the change and generating new possibilities (Bekar et al., 2018). Fourth, "There are no close substitutes"; it is not possible to substitute a GPT in many of its applications, since it is not available in the market another set of technologies able to produce similar effect, and this effect is a key component of the application, without it could not work properly (Bekar et al., 2018). Fifth, "Have a wide array of applications"; GPTs have various fields of application or a single generic use with many different business usages across many industries (Bekar et al., 2018). Sixth, "Initially crude but evolving in complexity"; it is difficult to date when a specific GPT was born, usually they begin with a single use since they are immature for a widespread adoption but with time they improve and become necessary in society (Bekar et al., 2018). The first three elements of the list refer mostly to the complementary effects that actions of a company on the technology have on the value of the technological assets of other players, while the following three elements focus on the scope of these complementarities. For sure the six characteristics are closely related one each other's.

Information & Comunication Technologies (ICT) is one of the most common examples of GPT (Bekar et al., 2018; Clarke, Qiang, & Xu, 2015; Jovanovic & Rousseau, 2005; Naughton, 2016). Even if it is impossible to find a unique and univocal definition, ICT refers to the set of technologies that makes possible the storage, elaboration and transmission of information. Even if storage and communication of information is possible since centuries through analog supports, it is just in the last decades that digital technologies allowed this process to exponentially scale up (Brynjolfsson, McAfee, Sorell, & Zhu, 2008) in the amount of information, or data, processed (Hilbert & López, 2011). **Internet** in particular is the network of networks making possible the communication among the computers connected thanks to Transmission Control Protocol (TCP)/Internet Protocol (IP) suite of protocols (Naughton, 2016; Postel, 1981b, 1981a). Born as a military experiment in the 50's it evolved to become the general purpose technology well known all around the world, enabling subsequent technological improvement and creating opportunities for new business to emerge (Naughton, 2016). Particularly, in the first decade of current century, it has been possible to witness to the trasformation into the "Web 2.0", in order to satisfy the growing request of tools able to launch e-commerce revolution (Naughton, 2016). The technology evolved in order to facilitate interaction between users and companies at first, and among different users lately (Naughton, 2016). Passing the years Internet became widespread among developed and developing countries, and new business models emerged consequently.

Digital Platform is a kind of business model made possible by ICT improvement during the first decade of current century (Acs, Song, Szerb, Audretsch, & Komlósi, 2021; Constantinides et al., 2018; Evans & Schmalensee, 2016; Zeng et al., 2021). The matchmaking mechanism representing the foundation of platform business model was not new, but the possibility to instantly store, elaborate and communicate to anybody almost infinite amount of information really made possible to scale the model to unprecedented level (Evans & Schmalensee, 2016). Matchmaking works by being able to connect supply and demand of a good or service through a platform, so the possibility to create value relies on the size of demand and supply the platform is able to reach (Evans & Schmalensee, 2016). The characteristics of this business model lead to the raise of few champions in each market, following a concept referred as "winner-take-all", since usually there is no space for many platforms in the same market due to network effects (Constantinides et al., 2018). This logic means the growth at the beginning is really important to increase the network size, success factor that could be more important that the technology itself (Schilling, 2002). ICT infrastructure really supported the growth of digital platform and constitutes a necessary element in the business model, that would not be feasible without it (Acs et al., 2021).

Artificial Intelligence (AI) has been identified as one of the currently developing GPT, greatly benefiting from ICT evolution (Brynjolfsson, Rock, & Syverson, 2017; Crafts, 2021; Klinger et al., 2018). AI has been defined as "*self-training structures of Machine Learning predictors that automate and accelerate human tasks*" (Taddy, 2018). AI has been categorized as a currently evolving GPT since the real potential is still unveiling, waiting for complementary innovation (Brynjolfsson et al., 2017). Artificial Intelligence has been recognized as an enabler for both business models and technologies (Armour & Sako, 2020; Milkau, 2019; Mishra & Tripathi, 2021).

Tourism industry is composed by the set of companies strictly interrelated horizontally, vertically and diagonally that put in practice the set of activities needed to satisfy all the requirements in term of travel, accommodation, nutrition and experience demanded by tourists (Fong, Hong, & Wong, 2021; Maggioni, Marcoz, & Mauri, 2014). Tourism industry is characterized by a strong interdependency among all the actors being part of the network of any given touristic destination, since they are mostly economically independent from each other (Buhalis & Spada, 2000) but the travelers evaluate and remember good or bad things related to the destinations they visit (Ritchie & Crouch, 2003). For this reason, the relationship of actors in tourism industry is often defined as coopetition (Fong et al., 2021). Coopetition describe the situation where there are two different forces, cooperation and competition, applied at the same time between two entities (Brandenburger & Nalebuff, 1996). In this case two competitors may cooperate in order to be able to reach to scarce resources (Doz & Hamel, 1998), that are the tourists in this case. The supply chain of tourism industry may be represented from different perspectives, one of the main ones is adopting the point of view of the tourist, in order to identify all the possible points of contacts during the customer journey (Fong et al., 2021; Romero & Tejada, 2011; World Economic Forum, 2017). The five phases characterizing the tourism supply chain from the customer journey perspective are the following: Travel inspiration, Booking and preparation, Transport services, Destination services, Post-trip (Filieri, D'Amico, Destefanis, Paolucci, & Raguseo, 2021; Fong et al., 2021; Romero & Tejada, 2011; World Economic Forum, 2017).

1.3.2 Theoretical framework

Technological improvement surely creates new possibilities in all sectors and industries (Chen, Chiang, & Storey, 2012). Information and Communication Technology for sure is a major force shaping the world we live in (Bekar et al., 2018; Clarke et al., 2015; Jovanovic & Rousseau, 2005; Naughton, 2016) and strongly impacts among the others also the tourism industry (Benckendorff, Xiang, & Sheldon, 2019; Bethapudi, 2013) with deep effects in each phase of the supply chain (K. Lee & Yuan, 2017). Information and Communication Technology based innovative business models are indeed able to reduce the cost and increase efficiency (Baden-Fuller & Mangematin, 2012).

We examined the relationship between general purpose technology-enabled innovative business models and the tourism industry from different perspectives and adopting different theoretical lenses. From one side Information and Communication technology empower entrepreneurs to use and propose digital solutions, allowing the creation of new business; in this regards literature is still evolving and there is a clear need of research deepening the stream of digital entrepreneurship (Elia, Margherita, & Passiante, 2020; Fu, Okumus, Wu, & Köseoglu, 2019; Kraus et al., 2019; Nambisan et al., 2019; Zaheer et al., 2019), the subject is deepened in Chapter 4. On the other side these entrepreneurs and these innovative business models trigger actions that have deep consequences on societies and economies; disruptive innovation theory is considered one of the most appropriate lens to examine the phenomena happening in hospitality industry due to technological innovation (Christensen, 1997; Guttentag, 2015; Guttentag & Smith, 2017; Valsamidis, Maditinos, & Mandilas, 2020) as illustrated in Chapter 2. Technological advancement is also changing the way touristic destinations as a system are managed in terms of required resources to be attractive (Denicolai, Cioccarelli, & Zucchella, 2010). Resource Based View (RBV) theory (Wernerfelt, 1984) adaptation to touristic ecosystems (Denicolai et al., 2010) highlights the primary activities needed by any touristic destinations to be competitive. As discussed in Chapter 3, Information and Communication Technology, enabling digital platforms business models, has completely changed and made more accessible the creation of accommodation facilities in touristic destinations and has created a completely new kind of intermediaries. Generally speaking the cost of discovering and reaching touristic destinations is decreasing (Adenwala, 2014; Franke, 2004; Wensveen & Leick, 2009), increasing number of travelers, but what are the characteristics of the players profiting and losing from these evolutions?

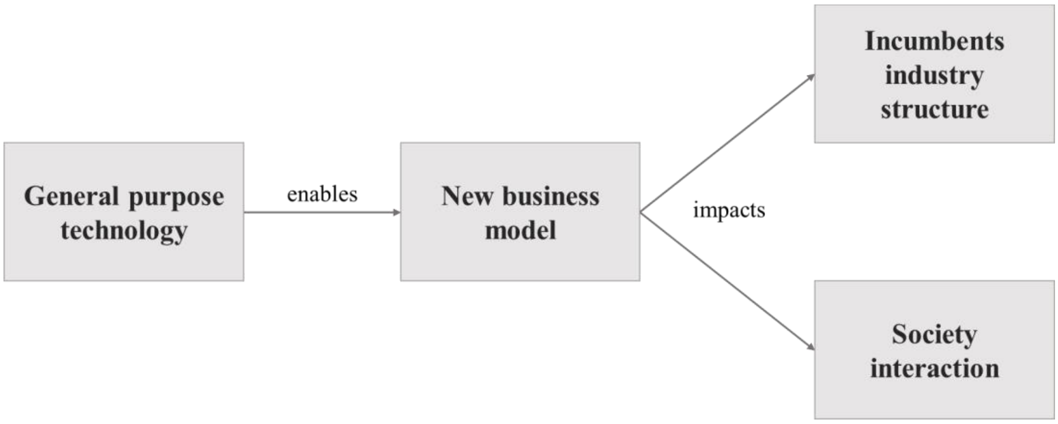

Figure 1: Theoretical framework

1.3.2.1. Management theories

Digital entrepreneurship refers to the stream of literature that studies how digital technologies make possible the creation of new innovation and entrepreneurial initiatives (Nambisan et al., 2019). These initiatives, made possible by technological improvement, foster entrepreneurship by facilitating communication among different industries weakening the boundaries among them, by lowering the cost of network creation and ultimately by accelerating the outset and scaling of new businesses (Lyytinen, Yoo, & Boland, 2016; Rayna, Striukova, & Darlington, 2015; Srinivasan & Venkatraman, 2018; von Briel, Davidsson, & Recker, 2018; von Briel, Recker, & Davidsson, 2018). Moreover, digital technologies push individual and companies to question about their current working methodologies and ways of communicating, fueling radical innovation processes (Nambisan, 2016; Nambisan, Lyytinen, Majchrzak, & Song, 2017; Yoo, Boland, Lyytinen, & Majchrzak, 2012). Digitalization pervasiveness seems to be reaching and changing almost every aspects of human society (Nambisan et al., 2019). Enhancing local entrepreneurship possibilities and enlarging economic and social growth by fostering competition are two examples of the consequences of digital technologies advancement and diffusion (Burtch, Carnahan, & Greenwood, 2018; Katz, Koutroumpis, & Callorda, 2014; Kenney & Zysman, 2016).

Digitization has overturned two previously strong assumptions that used to go with entrepreneurship studies. First, entrepreneurship results and processes used to be very restricted in their domain of applications, while digital technologies are weakening the boundaries making them much more unstable and permeable (Nambisan, 2016). Function is often separated from form and context and it is possible to leverage a great amount of flexibility in quickly experimenting, testing solutions and fixing eventual problems (Yoo, Henfridsson, & Lyytinen, 2010). On top of weakening the boundaries digitalization has increased the level of outcome unpredictability and nonlinearity of the process (Huang, Henfridsson, Ola, Liu, & Newell, 1999). Second, digitalization is enlarging and making unstable in time the set of entities involved in the creative process of generating entrepreneurial ideas, while in past time roles were more clear and fixed in time (Nambisan, 2016).

In the context of this thesis, the mechanisms behind digital entrepreneurship are the ones that allowed the creation of digital platforms business models like Airbnb (Hansen Henten & Maria Windekilde, 2016; Zaheer et al., 2019) and it is the theory that explain why artificial intelligence, direct evolution of digital technology, is going to change again the way companies make business and entities interact (Kazak, Chetyrbok, & Oleinikov, 2020; Mishra & Tripathi, 2021).

Disruptive innovation theory, originally developed by Clayton Christensen, explains one of the possible failure causes for established businesses leader of their industries due to emergence of simpler products or services (Bower & Christensen, 1995; Christensen, 1997; Christensen & Raynor, 2003). The theory describes a process where the introduction of a new, disruptive product or service is able to overturn the competitive equilibria in a market, resulting with the failure of the dominant companies (Bower & Christensen, 1995; Christensen, 1997; Christensen & Raynor, 2003). The main feature of a disruptive product is that it usually is simpler and less performing with respect to the characteristics of established products or services, offering consumers an alternative set of beliefs (Bower & Christensen, 1995; Christensen, 1997; Christensen & Raynor, 2003; Guttentag, 2015). It usually starts as a cheaper product or service, appealing the low-end of the market and even expanding the lower boundary to new segments (Bower & Christensen, 1995; Christensen, 1997; Christensen & Raynor, 2003). This is the less attractive part of the market from the perspective of the incumbents, since it is low in both size and margins, and they are even more pushed to keep on improving the product or service through sustaining innovation logic, towards the higher margin part of the market (Bower & Christensen, 1995; Christensen, 1997; Christensen & Raynor, 2003). With the passing of time the disruptive product or service improve its performance and its price, targeting even more the mainstream consumers, and pushing even more the incumbents towards the high-end, and now it is usually the moment those incumbents begin to struggle (Bower & Christensen, 1995; Christensen, 1997; Christensen & Raynor, 2003). In fact, many incumbents in this moment have spent huge resources to develop features interesting for a very small niche of customers, while the majority of their previous customers switched towards a simpler, more convenient alternative offered by the disruptor (Bower & Christensen, 1995; Christensen, 1997; Christensen & Raynor, 2003; Schmidt & Druehl, 2008).

In the context of this thesis, disruptive innovation is the theoretical lens that explains how the digital platforms, the innovative business model based on digital technologies advancement from the beginning of the century, are able to threaten the competitive position of the incumbents in hospitality and accommodation market.

Resource based view theory suggests that the characteristics of the resources in a company and the ability are key aspects in having sustainable competitive advantage in a market and that sustainable competitive advantage can be reached by companies through building and/or acquiring strategic resources and combining them (J. Barney, 1991; Wernerfelt, 1984). The resources above mentioned *"include all assets capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness"* (Daft, 1983) and are viewed as strengths available for carrying on a strategy (Porter, 1981). In more recent literature the scope of resource based view has been enlarged to consider not only competition among firms but also competition among systems or networks of firms that share similar goals (Denicolai et al., 2010). Tourism is a field where this concept fits very well, given the interdependence among many different entities living in the same touristic destination (Espino-Rodriguez & Padrón-Robaina, 2006; Hallin & Marnburg, 2008). Touristic destinations in fact, is composed by different entities independent from each other from a legal point of view but bound by strong interdependencies from a practical point of view (Buhalis & Spada, 2000). Since the tourist consider the destination as a single system (Ritchie & Crouch, 2003) the competitiveness of the destination depends on the inter-firm network configuration (Denicolai et al., 2010).

In the context of this thesis, resource based view is the theoretical framework explaining why the digital platforms are a mean able to improve touristic attractiveness of rural destinations.

1.3.3 Empirical framework

In order to investigate the research questions, this thesis focuses both on Italian hospitality market and on European tourism industry entrepreneurial ecosystem. The choice of the Italian hospitality market for the first part of the thesis is relevant because tourism and hospitality in Italy represent one of the biggest sources of GDP and employment, being Italy one of the most visited country worldwide. Italy in fact, was in last years the 5th country in the word by international touristic flows (World Tourism Organization, 2019), and travel and tourism industry represents one of the biggest sources of value production for the nation, being the 11.5 % of GDP in year 2017, 223 billion $ over 1935 billion $ (TUI, 2018). It is clear that travel and tourism industry represents a peculiar and fundamental feature of Italian economic system, and there is evident need of better understanding of what is currently happening under the surface and its consequences. More specifically the first part of the thesis takes into consideration two different contexts. The first is composed by the six most visited historical Italian cities characterized by the presence of both natural and cultural/artistic assets (cities characterized exclusively by tourism related to sea/mountain are excluded), that are Rome, Milan, Venice, Florence, Turin and Naples. The characteristics of these cities make the results generalizable with many others touristic cities with historical origins. The first part of the thesis is based upon a proprietary database that takes into consideration characteristics of the city, characteristics of the single hotel and Airbnb diffusion. All the data has been extracted from trustable sources, aggregated, merged and double-checked for unusual values that could indicate mistakes. The main sources used to collect the data are the following: ISTAT (the Italian National Institute of Statistics www. istat.it), AIDA (the main compendium of financial information on firms in Italy, distributed by Bureau Van Dijk, https://aida.bvdinfo.com/), AirDNA (the main data analytics company that provides data about Airbnb properties https://www.airdna.co/), Trustyou (the leading website that aggregates reviews from various sources regarding hotels https://www.trustyou.com/it/), TripAdvisor (the leading website that collect reviews and characteristics of hotels worldwide https://www. tripadvisor.it/). The raw data has been aggregated where necessary and merged in a single, treatable dataset panel (where hotels yearly changes are the unit of analysis). From this dataset has been possible to extract the growth in hotel profitability (delta ROS and ROA, the dependent variables), Airbnb capacity usage in central area of the cities (the independent variable), the attractiveness of the city position and the online reputation (the moderating variables) and all the controls. The dataset has been analysed through eight fixed-effect panel regression models with year-specific and hotel-specific effects to estimate the moderating effects of Attractiveness of the city zone and Online reputation on the direct effect of Central Airbnb capacity usage on the Growth of profitability of a hotel for the 2016–2018 period.

The second is composed by the set of the Italian "borghi", as defined by the association "I borghi più belli d'Italia". To be part of this association, that has the role of promoting and sustaining the touristic development of borghi, there are rules capping the size to a maximum level and requesting the presence of touristic assets, meaning this set is perfect for the analysis about digital platform impact. The thesis adopts a quantitative approach, carrying out fixed effect panel regressions in order to support the hypotheses. In this case the independent variable captures the diffusion of Airbnb solutions per city per year, while the dependent variables are the profitability of the independent hotels in the city and the touristic flow in the borghi. The main sources used to collect the data are the following: ISTAT (the Italian National Institute of Statistics www. istat.it), AirDNA (the main data analytics company that provides data about Airbnb properties https://www.airdna.co/), TripAdvisor (the leading website that collect reviews and characteristics of hotels worldwide https://www. tripadvisor.it/). The raw data has been aggregated where necessary and merged in a single, treatable dataset panel (where the Borghi yearly changes are the unit of analysis). All the data has been extracted from trustable sources, aggregated, merged and double-checked for unusual values that could indicate mistakes. In order to verify the formulated hypotheses, we ran 3 fixed-effect panel regression models with year-specific and hotel-specific effects to estimate the direct result of Airbnb supply growth on touristic arrivals and the moderation coming from the presence of the website.

The choice of European tourism industry entrepreneurial ecosystem for the second part of the thesis lies in the fact that European AI context is amongst the major players in the AI industry (Tractica, 2019). The complete Crunchbase (the largest database of funded start-ups, https://www.crunchbase.com/) set of Artificial Intelligence European start-ups has been analysed in order to extract the ones applying some specific kind of Artificial Intelligence domain in tourism industry. More specifically, a first step of screening analysed the website of the start-ups excluding the ones without references to tourism ecosystem. This result has been achieved thanks to a python scraper able to download the textual content of the websites. A similar scraper analysed the textual content of the resulting start-ups websites in order to keep only the start-ups targeting a specific tourism supply chain phase with a specific Artificial Intelligence domain of application. During this selection step the scraper also categorised the start-ups thanks to text analytics techniques. The authors double-checked the results in order to ensure the validity of the procedure. The scraper categorises the start-ups weighting the number of occurrences of set of keywords related to specific tourism supply chain phases and specific Artificial Intelligence domains of application. The obtained set of start-ups contains information about the founders, the investments received, the time and location of incorporation. Basing upon this set of start-ups, which have been categorised both on the axis of the phase of tourism supply chain targeted and on the Artificial Intelligence domain of application applied, the thesis adopts various techniques to answer the research questions, from time series to explore the trends currently happening to heat maps to represent the information extracted about promising technologies potentially changing specific phases of tourism industry supply chain.

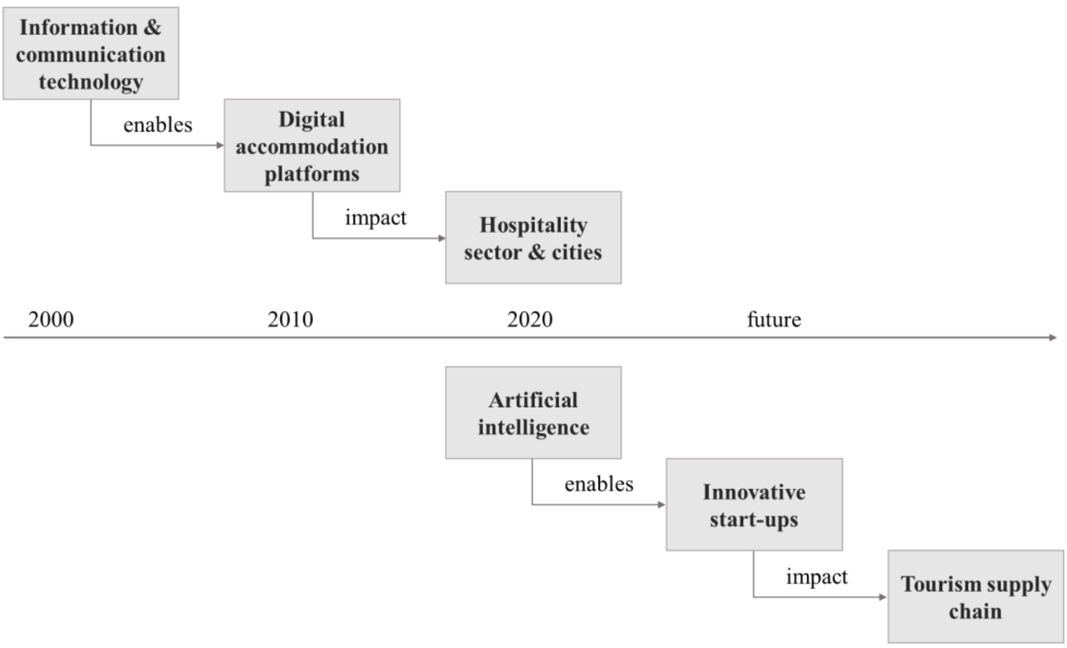

Figure 2: Empirical framework

1.4 Research findings and contribution

1.4.1 Independent hotels in historical Italian cities

Concerning the relationship between hotel sector and the service offered through digital accommodation platforms, this thesis starts from the assumption that there is a general substitution effect (Guttentag, 2015; Guttentag & Smith, 2017; Koh & King, 2017). Still, there is uncertainty regarding the moderating variables affecting this effect, past literature has extensively quantified the impact in many relevant researches (Akbar & Tracogna, 2018; Forgacs & Dimanche, 2016; Guttentag, 2015; Zervas et al., 2017), even finding situations in which the relationship is not significant or goes in favour of the hotels (Aznar, Sayeras, Rocafort, & Galiana, 2017; Blal, Singal, & Templin, 2018; Roma, Panniello, & Lo Nigro, 2019; K. L. Xie & Kwok, 2017).

This thesis focuses on a very specific context, the profitability of the independent hotels operating in the six most visited Italian cities with cultural and historic tourism, that are Rome, Milan, Venice, Florence, Turin and Naples. The context is specific but yet generalizable to most of European touristic cities. Under these conditions, the thesis found that the profitability if the hotels outside of city centre is significantly and negatively affected by the growing number of Airbnb solutions, while the profitability of the ones in the city centre is not significantly affected, meaning that possibly the Airbnb solutions in city centre are substituting the hotels outside of city centres. Moreover, conversely to what expected, the thesis found out that the online reputation of the hotels does not have any significant protection effect towards the profitability of the hotels, meaning that spending resources to reach the maximum reputation could not be the best strategy to follow for them.

1.4.2 Italian rural touristic destinations

Regarding the relationship between rural touristic destinations and the diffusion of solutions offered through digital accommodation platforms, the thesis begins distinguishing two very different contexts where digital accommodation platform solutions can spread: the touristic destinations already famous and the ones still developing. If on one hand in literature there are many papers underlining the disruptive effects of digital accommodation platforms growth on touristic ecosystem in well-known destination (Blal et al., 2018; Choi, Jung, Ryu, Kim, & Yoon, 2015; Dogru, Mody, & Suess, 2019; Dogru, Mody, Suess, McGinley, & Line, 2020; Zervas et al., 2017), on the other hand in less famous destinations digital accommodation platforms can have good economic benefit for local communities (Battino & Lampreu, 2019; Strømmen-Bakhtiar et al., 2020; I. P. Tussyadiah & Pesonen, 2016). In famous touristic destinations usually questionable phenomena like airification and gentrification of city centres happens (Diaz-Parra & Jover, 2020; González-Pérez, 2020; Wachsmuth & Weisler, 2018), but the small, less famous touristic destinations are protected from these negative externalities, at least in the short term, and they may benefit.

In the thesis the specific context of Italian “borghi” is analysed in terms of the effect of growing Airbnb solutions on the touristic flows, able to generate wealth in the community (Pröbstl-Haider, 2010; Pröbstl-Haider et al., 2014). The thesis finds a significant and positive correlation between the number of Airbnb solutions and the touristic flows, meaning that it can be considered an effective way for local communities to potentially attract touristic flows and the wealth that follows tourists.

1.4.3 Artificial intelligence start-ups in tourism industry

Finally, looking at the future, the thesis aims at paving the way for other researchers in measuring the consequences yet to come of artificial intelligence technology diffusion in tourism industry companies. The thesis begins with two assumptions: the first is that start-ups are a fundamental way for innovation to happen (Groen et al., 2008; Markides, 2006; Walsh, 2004), the second is that artificial intelligence is an enabler for new business models (Mishra & Tripathi, 2021). Given these premises it becomes clear that analysing the start-ups able to convince the market to finance them today it is possible to guess how the supply chain of a given industry will evolve, which parts will be more affected and by what kind of technology or business model.

In the thesis all the European start-ups applying artificial technology to a tourism related sector have been analysed in terms of the characteristics of the founders, of the kind of technology adopted and the part of supply chain of tourism industry targeted. Here are recapped the main findings of this section. According with previous literature, the set of start-ups is led mostly by male founders with experience in the industry in the European main start-up development hubs, but surprisingly the presence of higher education founders does not seem to be related to start-up success. The kind of start-ups collecting most funding are the ones related to any infrastructure, software and platform (e.g. cognitive computing; machine learning frameworks, library and platforms; chatbots and virtual assistants; internet of things) provided as (serverless) services or applications, possibly in the cloud, which are available off the shelf and executed on-demand, reducing the management of complex infrastructures, able to automatically learn, decide, predict, adapt and react to changes, improving from experience in order to identify, process, understand and/or generate information in written and spoken human communications. The phases of the supply chain targeted by these start-ups are the ones related to the services offered before and after the actual trip takes place.

1.5 Conclusions

Prior research has already started to deal with the impact of innovative business models on tourism industry from many different points of view, but analysing the literature we recognized 2 main areas the thesis aims at exploring: from one side there is much debate on the consequences companies and societies are currently experiencing from digital platforms diffusion in hospitality sector, on the other side there is a huge research stream at the crossing among entrepreneurship, artificial intelligence and tourism.

This thesis contributes to improve the knowledge in the first area with two main contributions, one related to the consequences that digital platforms diffusion is having on incumbent companies of the sector of hospitality, the second related to the consequences that the same diffusion is having on rural touristic destinations. The first main contribution is recognizing that the digital accommodation platform diffusion has a negative impact on hotels outside of city centres meaning the distance from the city centre is a fundamental variable to take into consideration both for researchers and managers. Moreover, we recognize the online reputation has no significant effect in moderating this relationship.

The second main contribution is shedding light on the potential role digital accommodation platforms can have in empowering rural communities in becoming successful touristic destinations, giving a way to entrepreneurs to create accommodation and reach audience interested in travel to the destination. The second area is a complete blue ocean with recent literature explicitly calling for contributions (Fu et al., 2019; Nambisan et al., 2019; Obschonka & Audretsch, 2020; I. Tussyadiah, 2020; Zaheer et al., 2019). The main contribution here is having explored the role of artificial intelligence as an enabling technology in tourism entrepreneurship, measuring the success in terms of investment received and recognizing both their antecedents and the most promising trends of innovation, that will change the structure of tourism supply chain in next years.

1.6 Thesis structure

The remaining of the thesis is structured as follows. Chapter 2 analyses the impact of the diffusion of the short rental sharing economy digital platform Airbnb diffusion on independent hotels profitability in Italian main historical touristic cities, highlighting the moderating role of the position of the hotel (in or outside city center) and the moderating role of its online reputation. Chapter 3 analyzes the impact of the short rental sharing economy digital platform Airbnb diffusion on the touristic flow in Italian rural destinations of “borghi”, highlighting the moderating role of their online reputation. Chapter 4 explore the characteristics of tourism AI start-ups, the AI technological domains financed by Venture Capitalists (VCs), and the phases of the supply chain where the AI domains are in high demand. Chapter 5 provides a summary of the research findings, the theoretical contributions, and managerial recommendations.

Chapter 2

The impact of Airbnb on hospitality incumbents

2.1 Introduction

The rise of the digital sharing economy platforms, which has been made possible thanks to ICT, has changed the way people make use of underutilized goods, and has also altered the competition dynamics between incumbents and new entrants in many sectors. One industry that has been revolutionized by the sharing economy more than others is the hospitality sector, as a result of the rise of many short-term rental platforms, such as Airbnb (Hansen Henten & Maria Windekilde, 2016). The way such platforms have entered the hospitality industry follows the dynamics of the disruptive innovation theory (Christensen, 1997). The incumbents, that is, hotels in the tourism sector, risk losing competitive ground for two reasons: first, due to the lack of an adequate strategic response and innovation capabilities to the competitive threats posed by disruptors and, second, due to the way they respond, that is, by improving service levels to serve customer segments with more complex needs.

It has already been analysed, in the recent research, how the rise of sharing economy platforms in the hospitality service industry has affected the performance of hotels (Blal et al., 2018; Dogru et al., 2019; Zervas et al., 2017). The outcomes present a picture of mixed results on how the availability of listings on Airbnb has an impact on the profitability growth of hotels. Such mixed results limit our understanding of the circumstances under which hotels suffer the least from the disruption effects that sharing economy schemes introduce into this industry, and they thus reduce our current understanding of the actions that hotels can enact to mitigate the threat posed by short-term rental platforms. Such mixed results are the consequence of a prevalence of empirical studies, which have been conducted in contexts with structural differences in the characteristics that affect the demand and the supply in tourism and the real estate markets at the local level. Apart from showing contrasting effects on estimating the impact of short-term sharing platforms on the performance of hotels, to the best of our knowledge, these studies do not consider the effective capability of hotels to cope with the competitive threats exerted by such disruptors as short-term rental sharing platforms. Accordingly, this study adopts a lens that is based on the disruptive innovation theory (Christensen, 1997) to investigate the effect of the diffusion of the leading sharing accommodation platform – Airbnb – on the performance of hotels in the vicinity. Specifically, we focus on two essential properties of the portfolio of resources and capabilities that hotels can deploy to cope with the disruption exerted by such new entrants as Airbnb. Such factors are the touristic attractiveness of the micro-zone in which a hotel is located within a city, and the extent of its ordinary capabilities, as reflected by the reviews generated by travelers on infomediary platforms. These two factors reflect the 'what to sell and where to locate' questions (Baum & Haveman, 1997; Sainaghi & Canali, 2011). Moreover, they have been highlighted as critical regarding the performance of hotels and their capability to survive in the long-term (Litvin, Goldsmith, & Pan, 2008; Ziqiong Zhang, Ye, & Law, 2011). Our aim has been to test whether these factors mitigate the competitive threats on profitability posed by disruptors, and whether these factors allow hotels to survive and prosper in times of disruption.

The first moderator we investigated for a hotel, namely its location in an attractive city zone, can be considered as a Ricardian rent, which is capable of appealing to a large number of customers and of granting cost advantages to some activities, such as sales and advertising, which can more than outweigh the higher costs related to real estate (Kivell, 1993; Montgomery & Wernerfelt, 1988; Prieto-Rodriguez & Gonzalez-Díaz, 2008).

The second moderator we investigated, that is, the online reputation of a hotel, is an ordinary capability that each hotel possesses. Specifically, ordinary capabilities refer to those capabilities through which a firm makes 'its living in the short term' (Winter, 2003) and which allow it 'to do things right' (Teece, 2014), namely to cope in a thriving manner with the industry's critical success factors. The ordinary capabilities in the hotel industry allow hotels to offer high service levels of traditional features, like managing the customer relationship, ensuring comfort and cleanliness and offering adequate amenities (Paiva & Vasconcelos, 2019). Although the awareness that arises from the disruptive innovation theory can in general have a limited effect on contrasting the competitive threat of new entrants, in a traditional sector, where room for innovation is limited, the conclusion may be different from what was expected. This is especially true for independent hotels, which are generally smaller than hotels in a hotel group, and are mostly made up of small-medium enterprises, many of which may not have the resources needed to invest in critical activities, such as research and development and workforce creativity improvements (Pikkemaat & Peters, 2006).

In short, the aim of the paper has been to answer the following research question: *To what extent can the rent positions, due to the attractiveness of a hotel's position and its online reputation arising from its ordinary capabilities, influence the impact of the diffusion of short-term rental sharing-economy solutions on independent hotels at a city level?*

The study has in particular focused on independent hotels located in the six historical cities with the highest touristic flows in Italy. In so doing, the present study contributes to the emerging literature debate on the economic impacts of the sharing economy on the incumbent hotel industry. From a managerial point of view, this study offers information to this specific category of hotels about the circumstances under which they become more vulnerable to the competition induced by such sharing economy platforms as Airbnb.

The contents of this chapter have been taken from a published paper to the Special Issue of the Current Issues in Tourism "Airbnb and the sharing economy" with the title "The impact of Airbnb on the economic performance of independent hotels: an empirical investigation of the moderating effects" (Destefanis, Neirotti, Paolucci, & Raguseo, 2020).

2.2 Theoretical background

2.2.1 Sharing platforms for short-term accommodation as a disruptive innovation

Sharing-economy digital platforms are reshaping industry structures and competitive dynamics in such sectors as mobility (e.g. Uber) and accommodation (Li & Srinivasan, 2019). This phenomenon is more evident in the accommodation sector, due to the entrance of players like HomeAway, VRBO, VayStays and Airbnb, who are focused on matching the demand and supply of short-term accommodation. Airbnb is the leading company in this market segment, with more than 6 million accommodation listings from 192 countries (Airbnb, 2019). Back in August 2017, Airbnb had more listings than the number of rooms built by the top five hotel brands combined (TOPHOTELNEWS, 2017). Airbnb makes the matching between hosts and guests possible, and charges a percentage of the daily cost. Guests pay a rate of between 6% and 12%, and this percentage decreases when several nights are booked, thereby making booking more convenient for longer periods, while hosts pay a fixed fee of 3% of the room price (Hansen Henten & Maria Windekilde, 2016). The sales revenues of Airbnb amounted to 2.6 billion dollars in 2017. Moreover, if the average intermediation fee applied were 12%, the value of the online transactions intermediated by Airbnb would surge to about 22 billion dollars.

The critical advantage of a sharing economy platform in tourism lies in its capability to orchestrate assets, such as rooms and apartments, when they are lying idle, thereby allowing the two sides of the platform to gain a mutual advantage in finding each other (Parker, Van Alstyne, & Choudary, 2016). A combination of different factors leads hosts to generally charge lower prices than hotels. They offer a lower level of service features to travellers, such as daily cleaning and breakfast, compared to the traditional service structure of a hotel, and a more flexible and scalable cost structure of the platform orchestrator and the hosts. Hotels in fact need to hire staff to work 24/7, in order to satisfy the strict regulations that are imposed, to pay higher taxes and to remunerate the shareholders' cost of equity capital (Chu & Choi, 2000; Dolnicar & Otter, 2003; Guttentag, 2015), while hosts may set a price that does not cover the long-term fixed costs, due to the capital invested or the extraordinary maintenance of their properties (Oskam, van der Rest, & Telkamp, 2018).

Several elements make the effects exerted by platforms like Airbnb on the competitive dynamics of the hotel industry fall in line with disruptive innovation, as conceptualized by Christensen in his theory (Christensen, 1997).

First, the worldwide diffusion of Airbnb listings follows the trajectory of the first half of an S-shaped curve, as shown in the AirDNA data plotted in Figure 3. Such a boost in the diffusion rate, after a flat beginning, is in line with the economic rules that characterize plat-form-based business models and multisided markets, such as the direct network externalities and the importance of complementary goods in the value transferred to the users on each side of the platform. By looking at the diffusion curve plotted in Figure 3, it is possible to note that the flat section lasts until at the end of 2011, when the rate of listing growth starts to accelerate; the adoption rate accelerates until the year 2015, when it stabilizes at circa 1.3 million new listings per year. It is also possible to notice the elbow of the curve between 2014 and 2015.

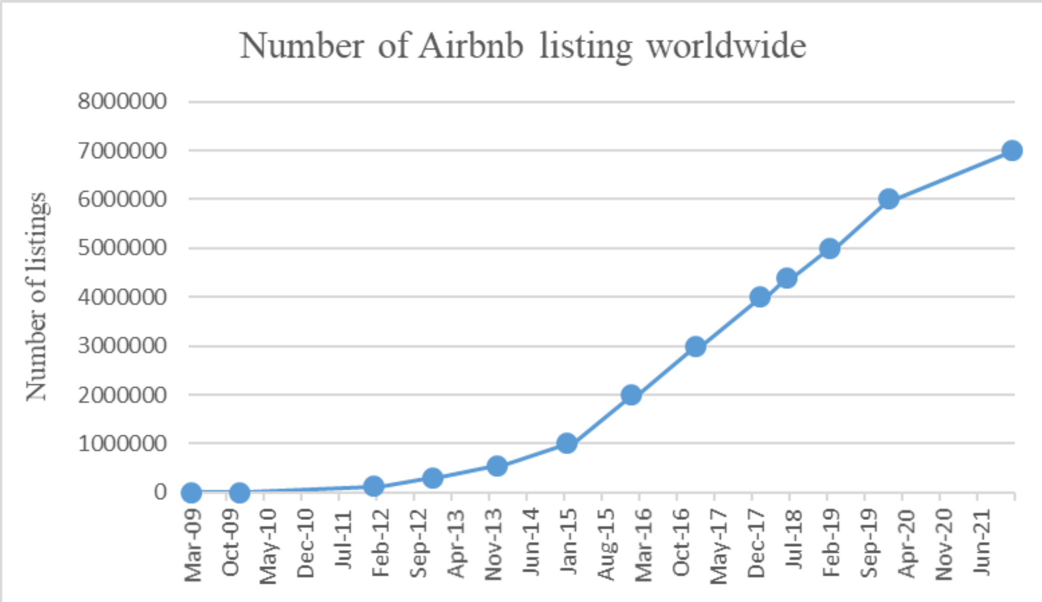

Figure 3: Number of Airbnb listing worldwide

Second, the way platforms like Airbnb have entered the market of short-term accommodation solutions and have generated a significant threat of substitution against hoteliers follows the dynamics theorized by Christensen and then underlined by Guttentag et al. in 2015 and 2017 (Christensen, 1997; Guttentag, 2015; Guttentag & Smith, 2017). Specifically, sharing economy platforms initially targeted a down-market, represented by travellers in search of cheap accommodation and with a limited willingness to pay for many of the amenities and features being offered by hotels, like daily cleaning of the rooms or wellness services (Chu & Choi, 2000; Dolnicar & Otter, 2003; Guttentag, 2015). In other words, the travellers that were initially attracted by platforms like Airbnb were not the same type of customers that were attracted to international hotel chains like the Marriott or Hilton, as it offered none of the good qualities of a hotel. In this vein, the first accommodation solution offered on the Airbnb platform was in fact just an air-inflated mattress in a living room in a students' apartment.

As Airbnb grew in popularity and in its capability to act as a listing orchestrator, it also started to provide diversified services and guidance to both travellers and renters, thus increasing the quality of its offering for both sides, as suggested in the Christensen theory (Christensen, 1997). Airbnb then began to address the needs of higher-value customers, who would otherwise have stayed at a nice hotel, and to offer them lower prices, which were made possible thanks to the flexibility of the new business model, as demonstrated by the introduction of a simultaneous review and certification system, a tool that had the aim of awarding the quality of the listings offered (Ert & Fleischer, 2019). Moreover, Airbnb has been able to provide superior performance, pertaining to the services and features needed to create memorable experiences, due to the greater rigidity that arises from the high fixed cost that is typical of the business model used by hotels (Kotas, 1982; Mody, Suess, & Lehto, 2017). In the same way, Airbnb is able increase its room capacity in a faster and cheaper way than any hotel, as a result of the flexibility of its plat-form-based business model (Roma et al., 2019; Zervas et al., 2017), putting into practice the 'scale without mass' principle theorized by Brynjolfsson et al. (2008), which is at the base of the competitive advantage of many digital companies (Brynjolfsson et al., 2008). The points discussed so far are summarized in Table 2.

Table 2: The disruptive innovation characteristics of Airbnb

	The beginning of Airbnb 2008 – 2010	**Airbnb after some years 2011 – 2015**	**Airbnb today 2016 - 2021**
Performance level	Air-mattress in living room in a shared apartment	Enlarged range of services	Business-oriented services; Airbnb Plus
Prices	On average cheaper than hotels	Covering all price ranges	Covering all price ranges, attacking the high-end market
Diffusion	Slow diffusion rate	Quick acceleration of the diffusion rate	Stable diffusion rate

In formulating his general disruptive innovation theory, Christensen observed that, in many cases, the incumbent's reaction to the disruption caused by a new entrant is to offer 'services that are actually too sophisticated, too expensive and too complicated for many customers on their market. […] However, by doing so, companies unwittingly open the door to 'disruptive innovations' at the bottom of the market'. An innovation that is disruptive allows a whole new population of consumers at the bottom of a market access to a product or service that was historically only accessible to consumers with a great deal of money or skills (Eckert, 2019). The disruptive innovation theory indicates two possible ways for hotels to respond to the disruptor: shifting their focus to higher market segments or replicating and perfecting the disruptor business model (Christensen & Raynor, 2003; Guttentag, 2015).

A clear picture of the responses introduced by hotels to fight the phenomenon is still missing in the recent literature, and most of the researches carried out through interviews indicate that hotels do not consider sharing economy platforms as a threat, and are behaving as the disruptive innovation theory suggests (Choi et al., 2015; Koh & King, 2017). On the other hand, some large international chains are exploring business innovations that can positively affect their cost position, their differentiation potential and their scalability. For example, the Marriott group has launched a section of the website where it is possible to book 'moments' (https://moments.marriottbonvoy. com/), something similar to the 'experiences' page of the Airbnb website, and has created a platform for certain high-end short-term rentals (https://homes-and-villas.marriott.com/).

2.2.2 The impact of a short-term rental sharing economy platform on the performance of hotels

The previous literature has clearly demonstrated that, in part due to the growth of sharing platforms in the accommodation industry, the economic performance of the hotel sector is now decreasing (Akbar & Tracogna, 2018; Forgacs & Dimanche, 2016; Guttentag, 2015; Zervas et al., 2017). By looking at the general global trends in the travel industry, it is possible to see how hotel revenues increased between 2015 and 2017 at a lower rate (+ 8% vs +11%) than the revenues produced in the travel and tourism industry as a whole (TUI, 2018; WTTC, 2018).

Notwithstanding the threat of the sharing economy to hotels, the growth in economic importance of sharing platforms in the accommodation industry has not yet been accompanied by univocal firm-level evidence about a negative impact of the local supply of listings on sharing platforms on the profitability of hotels.

The impact of short-term rental sharing economy platforms has already been studied, mostly focusing on Airbnb, the most successful platform, on the hotel industry, but contradictory evidence has emerged (Appendix 1). Zervas et al. (2017) demonstrated that a 1% increase in Airbnb supply decreased hotel revenue by 0.04% in Texas (Zervas et al., 2017). Dogru et al. (2019) studied the phenomenon in 10 of the main U.S. cities and demonstrated that an active supply of entire homes impacted hotel RevPAR (Revenue Per Available Room) and ADR (Average Daily Rates) by 0.02%, with a significant effect on all the hotel segments (Dogru et al., 2019). Roma et al. (2019) also observed a significant impact of Airbnb supply on hotel pricing; they showed how the price is mostly constrained during weekends and for the lower star categories (Roma et al., 2019). On the other hand, even though most of the researches have highlighted a negative impact of the diffusion of the sharing economy on the performances of hotels, some results show a different picture. In the next sections, we report details of all the factors that can lead to a positive or insignificant impact on the performances of hotels, in contrast to the negative effect found in the majority of available researches.

The first factor that has a positive effect on the performance of hotels is the average price of the Airbnb listings in the same city (Blal et al., 2018). Observing the RevPAR of hotels and the average Airbnb listing prices in the city of San Francisco at 11 time instants, between December 2013 and February 2018, they found that a higher RevPAR was correlated with a higher average price of Airbnb listings. Moreover, in the same research, the hotel segment was identified as a positive moderating factor, which means that five-star hotels obtain significantly more benefit from the average price of Airbnb listings. The same result emerged after examining the output of research carried out on thirteen of the most important touristic cities in Italy, where it was found that a high penetration of Airbnb listings had a detrimental impact on the pricing level of 1, 2 and 3 star hotels during the weekends, with high-end hotels (4 and 5 stars) not being affected to any great extent (Roma et al., 2019). On the other hand, this latter factor, that is, the hotel segment, has also been found not to have a significant effect on the ROE of hotels in Austin and Barcelona. Researchers in Austin analysed the impact of the number of Airbnb listings in the same Postal code area on the hotel RevPAR (K. L. Xie & Kwok, 2017). The direct relationship between them showed a negative correlation, but the hotel segment was found not to be a significant moderator of the relationship. Researchers in Barcelona collected balance sheets from a sample of hotels from 2008 to 2013 and found that the hotel category was not significantly correlated with the ROE (Aznar et al., 2017). In the same paper, the authors also studied the correlation between ROE and the presence of Airbnb listings within a radius of 1 km from a hotel, and found a positive and significant correlation. In this case, the high number of Airbnb listings behaves like a proxy of the attractive location of the hotel. The last positive relationship was found in the kingdom of Swaziland, in Africa, where a positive correlation between the Airbnb occupancy rate and the hotel occupancy rate was found in the four main cities, which were investigated from 2012 to 2016 (Ginindza & Tichaawa, 2017). The reason for this phenomenon probably lies in the different phases of tourism development the country has been undergoing and it is within this specific context of a developing country, with a growing tourism and accommodation sector, that the authors show us different markets for hotels and Airbnb and conclude that the two products can be viewed as non-competitors.

The first factor Xie and Kwok (2017) found to not have a significant impact on the relationship between hotels and Airbnb is the online rating of the hotels (K. L. Xie & Kwok, 2017). The authors used the variable as a moderator between the supply of Airbnb listings in the same Postal code area and the RevPAR, but they found no evidence of a moderating effect. The authors suggested that Airbnb listings remain equally noticeable substitutions for hotels across all the perceived rating scales. The second factor that has not shown any significant effect is the total Airbnb supply (Blal et al., 2018; Choi et al., 2015), when tested in the city of San Francisco and in the main Korean cities, regarding the presence of hotels. The last factor we have considered is the size of the hotel, which was shown to not have a significant impact on the city of Barcelona (Aznar et al., 2017).

The analysis of these studies highlights the lack of a clear conclusion about the impact of the offered local supply of listings on the sharing-economy platforms on the performance of hotels and seems to suggest that some hotels are suffering from this new form of competition, whereas other hotels do not seem to be particularly affected. From a theoretical standpoint, this issue is related to the fact that some companies are more able than others to cope with the disruption ignited by new entrants, and that there may be critical contingent factors that could explain the impact of Airbnb on the performance of independent hotels. These include the features of the local market where the hotels operate (hotel positioning) and the ability of a hotelier to manage changes in the tourism sector (hotel's capabilities). These two contingent factors are considered in this study, since they are the main critical success factors in the hospitality and accommodation industry (Baum & Haveman, 1997; Sainaghi, 2011). Their importance and effect on the investigated relationship are discussed in the following sections.

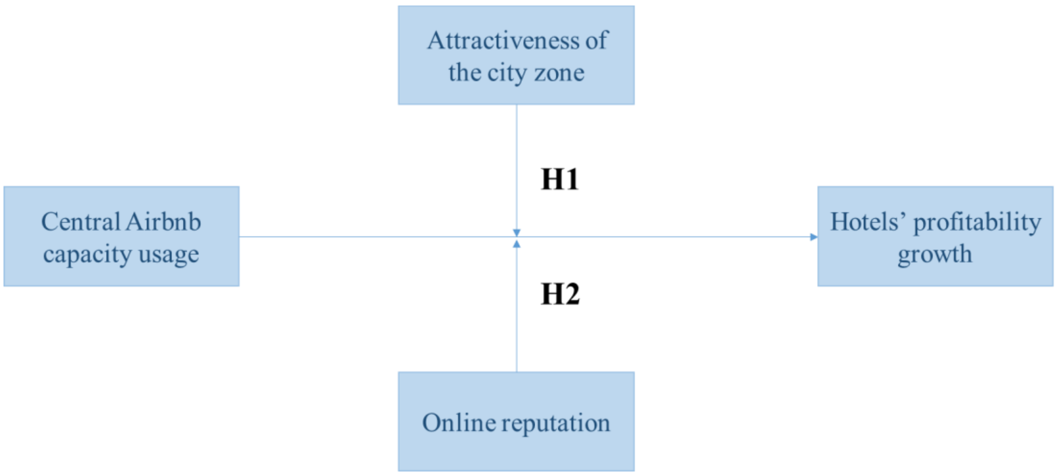

Figure 4: Research framework

2.3 Hypotheses development

The critical contribution of this study lies in assessing how ordinary capabilities that are reflected on a hotel's reputation and the attractiveness of their position allow hotels to cope with the diffusion of Airbnb's short-term rental solutions at the city level (Figure 4).

The zone of the city where the hotel is positioned has been demonstrated to have an impact on the performance of hotels (Baum & Haveman, 1997; Egan & Nield, 2000; Lado-Sestayo, Vivel-Búa, & Otero-González, 2020; Sainaghi, 2011; Yang, Luo, & Law, 2014), since travelers desire proximity to the points of interest (e.g. museums, important architecture) and local transportation systems (Masiero, Yang, & Qiu, 2019). It has been shown that the entrance of landlords into the accommodation market is higher in city centers or zones that have a high tourist attraction (Zhihua Zhang & Chen, 2019). This economic behavior may be due to the higher demand for accommodation in these types of areas, which is caused by aggregation economies due to the higher concentration of touristic points of interest and the lower costs borne by customers to access them. In historical European cities, such as the ones in our setting, these points of interest are generally located in the city centers (Diaz-Parra & Jover, 2020; González-Pérez, 2020) and, following an approach based on a mono-centric model, this is why we have assumed that these areas can be regarded as 'highly attractive' and the territory outside these areas as relatively 'less attractive'. In other words, since the central location of a hotel is a valuable resource that is challenging to imitate and almost unique, due to the scarcity of free space in city centers, we consider it as a Ricardian rent, which is able to grant performance advantages with respect to hotels outside of the attractive zone (Montgomery & Wernerfelt, 1988; Prieto-Rodriguez & Gonzalez-Díaz, 2008). These hotels located in the central area, due to the nature of the Ricardian rent granted by their position, may face lower operational costs than competitors for using their assets, and have better financial results and/or more freedom to fight against the disruptor as a result of the considerably greater amount of resources available (J. B. Barney, 1986). The higher endowment of resources may essentially be due to two factors. First, a hotel's capability to follow benefit differentiation logics for the customer, due to the presence of aggregation economies that endow the hotel with the possibility of offering memorable experiences to its customers, thanks to a more prosperous and more proximate value network (Hamel, 2002; Kandampully, 2006). Such a value network is made up of restaurants, museums, theatres, stores and local transportation systems. Second, independent hotels located in attractive city zones have usually been in existence longer and are usually run by families; this implies that, in some cases, they have already borne some of the costs related to real estate (J. B. Barney, 1986; Glancey & Pettigrew, 1997).

However, there is another perspective linked to the disruptive innovation theory that can explain why hotels at present located in city centres can suffer less from the competitive threats posed by sharing-economy schemes. In fact, the entry of the disruption into city centres and the most attractive zones is higher. In other words, the listings of hosts on sharing platforms are mainly concentrated in city centres because of the greater attractiveness of the area and the higher sunk cost borne by landlords (Quattrone, Greatorex, Quercia, Capra, & Musolesi, 2018; Zhihua Zhang & Chen, 2019). The cost advantage of hosts that list their assets on platforms, such as Airbnb, implies that the price of listings in zones with high touristic attractions may be comparable with that offered by hotels that are located outside the most attractive areas in a town, and may even be lower than the price of hotels in the city centre, but offer a higher level of service (Zhihua Zhang & Chen, 2019). This is in line with the disruptive innovation theory, where the disruptor starts eroding the accommodation market with lower prices and lower levels of offered service, and slowly begins to grow while impacting the mainstream market across hotel class segments (Dogru et al., 2019; Guttentag, 2015; Zervas et al., 2017). In other words, we contend that short-term rental sharing-economy platform listings in zones with high touristic attractions represent an alternative to hotels in semi-central areas that is equivalent in terms of price. This implies that hotels outside urban micro-zones with high touristic attractiveness may be the ones that suffer the most from the availability of rooms and apartments in the city centre. On the basis of these considerations, we have formulated the following hypothesis.

H1. *The attractiveness of the city zone where a hotel is located positively moderates the effect that the diffusion of home-sharing platforms has at the city level on the hotel's profitability growth, with hotels located outside the most attractive zones suffering the most.*

The second critical success factor we have focused on is based on how well hotels run their core activities, as seen through the eyes of the guests and from the satisfaction they express in rating a hotel on traveller-generated review aggregators like Tripadvisor (Anderson & Sullivan, 1993; Lehto, Park, & Gordon, 2015). There are multiple reasons why ordinary capabilities can reflect on the reputation associated with traveller reviews, and why they could be considered as a moderator of the relationship between the presence of Airbnb and the profitability growth of a hotel.

First, the capabilities necessary to achieve a high online reputation are somewhat ordinary (Schuckert, Liu, & Law, 2015), that is, they are related to ‘the performance of administrative, operational and governance-related functions that are (technically) necessary to accomplish tasks’ (Teece, 2014). Accordingly, a hotel’s online reputation measures how well the hotel runs its core activities.

Second, reputation, as an outcome of a hotel’s ordinary capability, plays a central role in attracting travellers, as it acts as a mitigation factor of the information asymmetry between hoteliers and customers (Schuckert et al., 2015). In other words, in industries where rankings are available, this information acts, according to customers, as the outcome of a firm’s ordinary capabilities. In the case of hotels, the relevance of rankings and reviews has to do with the fact that hospitality belongs to the experience goods category, and its value can only be assessed when the service has been consumed. The online reputation of hotels with no brand (i.e. the majority of small hotels that are not part of an international chain), stemming from travellers’ reviews, is a substitutive mechanism of the brand (Hollenbeck, 2018), which is able to address the choices of travellers about where to go and stay. Moreover, a hotel’s reputation can reflect various phenomena that are related to a hotelier’s superior managerial capabilities in offering hospitality services and managing customer relationship in the online world (Schuckert et al., 2015).

Third, positive customer rankings and reviews represent something ordinary that provides an accepted standard of hospitality and, in the eyes of the potential customers, a good reputation is something that is expected (Schoenmueller, Netzer, & Stahl, 2018).

Provided the reputation reflects the extent of a hotel’s ordinary capabilities, and for the reasons explained above, we contend that such a factor could be a way for hotels to contrast the business-model innovation capability of such disruptors as home-sharing platforms, and could allow the negative effect of Airbnb on the profitability growth of hotels to be moderated. Thus, we posit:

H2. *The online reputation of a hotel positively moderates the effect that the diffusion of home-sharing platforms has at the city level on the hotel’s profitability growth, with lower online reputation hotels suffering the most.*

2.4 Methodology

The data collection involved a sample of 725 independent Italian hotels located in Rome, Milan, Venice, Florence, Turin and Naples. We chose these six cities because they are the six most representative artistic and historical cities in Italy regarding touristic flows, according to ISTAT data (www. istat.it). All the selected hotels were listed on the AIDA database (distributed by Bureau Van Dijk, https://aida.bvdinfo.com/), which is the main compendium of financial information on firms in Italy. The data for this research were also obtained from the TripAdvisor website (https://www. tripadvisor.it/), from AirDNA, a data analytics company that provides data about Airbnb properties (https://www.airdna.co/), from Trustyou, a website that collects reviews from various sources regarding hotels (https://www.trustyou.com/it/) and from ISTAT, the Italian National Institute of Statistics (www. istat.it).

The choice of focusing the empirical analysis on urban areas is in line with the focus that literature has had on the theme so far. As discussed in previous research, cities, rather than small towns, is the setting where the threats of sharing platforms may be higher, due to a tougher competition of resource, such as space, and a higher concentration of people (Sun et al., 2018).

Before running the models, all the data underwent an extensive cleaning process that is summarized hereafter. The starting point was the extraction of balance sheet data pertaining to all of the 17,234 Italian companies registered as hotels in the AIDA database ('Alberghi' category, ATECO code: 55100). We filtered the hotels' balance sheets and kept the ones that had their operating address in the selected cities. Since the address recorded in the AIDA database is not always the same address as the structure where the business takes place, we double-checked the position by looking at the VAT number on the web to be sure the financial data referred to a single hotel in one of the six cities under investigation. In this way, all the balance sheets referring to hotels not located in one of the six cities or related to more than one structure were deleted from the sample. This decision is justified by the fact that one of our targets was to analyse the relationship between the location of a hotel and its performance; considering economic measures that refer to a variety of hotels that aggregate financial results would lead to bias. Moreover, different effects of online reputation on hotels that are a part of a branded chain and on hotels without a brand have been shown in previous research, and the choice of focusing on independent hotels has therefore allowed us to explore the moderating role of online reputation, without any possible distortion arising from hotels that are part of a chain (Raguseo & Vitari, 2017). In this phase, we gathered the geographic coordinates of each hotel in order to pinpoint its exact location in the city.

After this phase, each selected hotel was linked to its TripAdvisor page, from which we extracted information about the services offered, and to its Trustyou page, to obtain the score that represents its online reputation. We merged the gathered data with the Airbnb data provided by AirDNA.

These data underwent a similar process: we counted the total number of equivalent and active Airbnb listings for each city and each year, and their actual usage by customers. We also triangulated the data with the ISTAT database from which we gathered some of the control variables included in the model, such as touristic flows, hotels in the city and size of the city. Given the availability of Airbnb data for three years, that is, 2016, 2017 and 2018, we finally built a panel dataset of 725 hotels that spanned the period of these three years.

2.4.1 Measures

Table 3 summarizes the information about the operationalization, data source and reference of each variable considered in this study.

Table 3: Operationalisation of the independent and the dependent variables

Type of variable	Construct	Sub-construct	Operationalisation	Data source	References to previous studies
Dependent variable	Growth in hotel profitability	Delta ROA	Difference between the income/total assets of the current year of operation and that of the previous year	AIDA	Qian and Li 2003
		Delta ROS	Difference between the income/sales revenues of the current year of operation and that of the previous year	AIDA	Qian and Li 2003
Independent variable	Central Airbnb capacity usage	-	Number of booked nights in the city centre * number of bedrooms	AirDNA	Dogru, Mody, and Suess 2019
Moderating variable	Attractiveness of the city zone	-	Dummy variable equal to 1 if the hotel is located in the city centre, and 0 otherwise	Elaboration on AIDA, TripAdvisor and Google Maps data	Ziqiong Zhang, Ye, and Law 2011
	Online reputation	-	Logarithm of the cumulative average review score	Trustyou	Litvin, Goldsmith, and Pan 2008

Control variables	Touristic flows	-	Logarithm of the number of nights spent in a hotel	ISTAT	Zervas, Proserpio, and Byers 2013
	Hotel capacity	-	Logarithm of the number of rooms in a hotel	ISTAT	Lee and Jang 2012
	Hotel competition	-	Logarithm of the number of hotels with the same number of stars in the city	ISTAT	Becerra, Santaló, & Silva, 2013
	Restaurants near the hotel	-	Number of restaurants in a radius of 500 meters from the hotel	TripAdvisor	Terhorst & Erkuş-Özturk, 2011
	Hotel star category	-	Number of stars of the hotel	Hotel website	Aznar, Sayeras & Alba Rocafort, 2017
	City size	-	Logarithm of the number of inhabitants (number of residents) in a city	ISTAT	Zervas, Proserpio, and Byers 2013
	Age of the hotel	-	Logarithm of the number of years of operation of a hotel	AIDA	Stinchcombe, 1965
	Business-friendly hotel	-	Dummy variable equal to 1 if the hotel has services related to business customers	TripAdvisor	Mccleary, Weaver, & Hutchinson, 1993

Note: n.a. stands for "not available"

Dependent variable

Hotels' profitability growth. The considered dependent variables are the differences from the previous year of two of the most frequently used profitability indexes: Return On Sales (ROS) and Return On Assets (ROA) of the hotels (Qian & Li, 2003). We use two variables, because a single measure may have generated criticism (Weiner & Mahoney, 1981). Both variables are obtained from the Bureau Van Dijk financial database, AIDA.

Independent variable

Central Airbnb capacity usage. This construct refers to the total number of room-nights booked in Airbnb listings in the attractive area in a year in the city under analysis (the definition of attractive area is discussed extensively in the description of the next variable, that is, 'attractiveness of the city zone'). We elaborated this variable using data from the AirDNA database. This operationalization is different from the typical way extant studies have operationalized the diffusion of Airbnb. There is in fact a tendency, in the extant studies, to focus on the number of active Airbnb listings as an expression of the available supply of rooms at the city level (Dogru et al., 2019; Zervas et al., 2017). Instead, in this study, we operationalized Airbnb as the product of the number of booked nights per listing per year and the number of bedrooms available in a listing. Therefore, this metric refers to the room's capacity, as orchestrated by the platform, which is actually used by the tourists. This variable was normalized to compute its interaction effect with the two moderating variables.

Moderating variables

Attractiveness of the city zone. The first moderating variable describes the location of each hotel with respect to the city centre, since, in previous literature, the position emerged as a possible source of hotel differentiation that led to higher profitability (Baum & Haveman, 1997; Sainaghi, 2011; Ziqiong Zhang et al., 2011). The Attractiveness of the city zone was operationalized with a dummy variable equal to 1, when the hotel was located in an attractive district, and 0 otherwise.

The selected cities, for historical reasons, are all characterized by a high concentration of tourist points of interest in their central areas. In the past centuries, in fact, the central area represented the political heart of urban aggregation and collected most of the powerful and influential people, who were usually the same ones who cared about the works of art, architecture and beauty that we can nowadays admire in many museums, squares and gardens (Diaz-Parra & Jover, 2020; Purcell, 2014). Therefore, we identified the central area as being the most attractive in each city. Furthermore, the central areas in many cities are perceived by tourists as the safest and most well-maintained places, where the probability of having any problem (e.g. robberies) is minimized. Tourists generally prefer to stay in such areas, or reasonably close to them, that is, at a distance of a few minutes on foot, and the satisfaction of being in such a zone is very high, close to the maximum possible (Russo, 2002). Satisfaction decreases in zones just outside the 'best zone', because the time taken to reach the points of interest increases, and it may be necessary to use different means of transport to reach such areas, thus incurring expenses.

In order to operationalize the variable, we adopted the mono-centric model, which has the aim of describing land use patterns with two or more mono-centric rings, using the distance from the city centre as a discriminating factor, on the 'assumption that tourists are willing to pay more in return for easy access to the city centre' (Shoval, 2006; Yang et al., 2014; Yokeno, 1968).

To identify the area that refers to the city centre and therefore to the attractive zone, we identified the zones where the main touristic attractions are by using Google Maps to visualize them. After this step, we were able to trace a circle around each city centre that included the main touristic attractions. The radius of this circle was equal to 4 kilometres for Rome, 2 kilometres for Milan, 1.85 kilometres for Venice, 1.4 kilometres for Florence, 1.7 kilometres for Turin and 1.75 kilometres for Naples. The circles we located were then used to divide the hotel sample into two sub-samples, the hotels inside the circles (which were considered to be in the city centre) and the ones outside (which were classified as outside the city centre). In other words, the circles were drawn to include the main touristic attractions and the hotels close to them. This variable was normalized to compute its interaction effect with the independent variable.

Online reputation. The online reputation variable was operationalized through the cumulative average review score of a hotel from several trusted online sources. This information was taken from Trustyou.com, a portal that collects and aggregates all the certified reviews available on the web about hotels. The travellers' rate on this website is established on a five-point scale, where the scores are 'terrible', 'poor', 'average', 'very good' and 'excellent'. We chose the review score instead of the volumes of reviews since most of the earlier studies had found that the former is the dimension of a hotel's visibility that has the most impact on sales (Garrido-Moreno, García-Morales, Lockett, & King, 2018) and profitability (Litvin et al., 2008). Finally, online reputation was normalized to compute its interaction effect with the Airbnb capacity usage variable.

Instead, the variable is used in the post hoc analysis as a threshold to test whether a very high online reputation could behave as a moderator. Specifically, we test threshold values of 4.1, 4.3, 4.5, 4.7 and 4.9. In all these cases, we defined a new variable with a value of 1, if the reputation was higher than the threshold, and 0 otherwise.

Control variables

Touristic flows. The touristic flows were operationalized as the number of cumulative nights tourists spend on accommodation in the city under analysis. The considered data were taken from the ISTAT database, and allowed us to control for the total size of the touristic phenomenon (Zervas et al., 2017). The natural logarithm form of this variable was computed, since it made its distribution closer to a normal one.

Hotel capacity. The hotel capacity was considered in terms of the number of rooms. These data were collected from the TripAdvisor pages of each hotel, and they are a proxy of a hotel's supply size (S. K. Lee & Jang, 2012). The natural logarithm form of this variable was computed, since it made its distribution closer to a normal one.

Hotel competition. We modelled the internal competition the hotels face with the number of the same category hotel rooms in the city in the same year. This variable has the aim of controlling for direct competition in the model (Becerra, Santaló, & Silva, 2013). The logarithm of that number was used in the models, since it made its distribution closer to a normal one.

Restaurants near to a hotel. The number of restaurants in the vicinity of a hotel (within a 500 metre radius from the considered hotel) represents a proxy of the complementary services tourists can find in a city in the zone surrounding the considered hotel. Restaurants are part of the same system as hotels, and they act as a complement by reinforcing the competitiveness of a hotel (Terhorst & Erkuş-Özturk, 2011).

Hotel star category. As part of the main distinguishing characteristics of hotels, we included the category pertaining to the official star rating, as already used in the previous literature (Aznar et al., 2017). The aim of this variable is to control for the different effects that stem from different types of hotels, with different prices, services, and customer targets.

City size. We included the number of residents in each city, as taken from the ISTAT database, as a proxy of the development that the city itself has reached (Zervas et al., 2017). The natural logarithm form of this variable was computed, since it made its distribution closer to a normal one.

Age of the hotel. We operationalized the age of hotels by measuring each hotel from its year of foundation. Specifically, we extracted the year of establishment of each hotel from the AIDA database and calculated its age. The effect of age on profitability may be either positive or negative: on one hand, older firms should have more experience, and this can lead to superior performance; however, older firms may not have the flexibility required to adapt to rapid changes in market conditions, thus, exhibiting lower performances than younger firms (Stinchcombe, 1965). The logarithm of that number was used in the models, since it made its distribution closer to a normal one.

Hotel business friendly. Different proxies have been used in the recent literature to measure whether a hotel is able and willing to welcome business customers or not. Business and leisure travellers differ in the way they purchase their accommodation solution, with the former usually having the freedom to choose any destination hotel they want using the budget offered by the company; this feature should therefore be controlled for (Mccleary, Weaver, & Hutchinson, 1993). In our studies, we modelled this variable, considering TripAdvisor data, by looking at the presence of three business-oriented facilities (Zervas et al., 2017): meeting room, conference hall and convention centre. If a hotel had at least one of these facilities, is was considered business-friendly, and the dummy variable was equal to 1, and 0 otherwise. We collected the business-friendly facilities from the TripAdvisor page of each hotel.

2.4.2 Sample composition

Table 4 shows the composition of the sample. We selected the six historical cities in Italy with the highest touristic flows. They are all characterized by a high number of nights spent by tourists during the year, even though Naples and Turin are not at the same scale as the other cities. Milan, Turin and Naples have populations of around 1 million each, while Florence and Venice have much smaller populations, even though their touristic flows are comparable with those of Milan. Rome is by far the city with the highest population and touristic flows. The massive number of tourists, compared to the relatively small population in Florence and Venice, could lead to the emergence of the 'touristification' phenomenon, which has a profound impact on the residents (Sequera & Nofre, 2018). In the sample, there are more hotels in Rome; Milan, Venice and Florence are at the same scale, with a moderate number of hotels, while Turin and Naples are behind the other cities from the touristic offer point of view. As expected, the number of hotels is proportional to the touristic flows, regardless of the size of the city, thus confirming the existence of a more pronounced 'touristification' phenomenon in the smaller cities with high touristic flows, than in the larger cities impacted less by tourism. As mentioned above, only independent hotels, where the balance sheet data are linked to a single structure, were considered in the sample of hotels. This design choice has had the dual objective of univocally geo-referencing the considered financial data and of analysing the specific category of hotels that does not have a brand strategy to follow and instead takes all the decisions in complete autonomy.

Table 4: City statistics

City	Number of residents in 2017	Touristic flow in 2017 (nights spent in a hotel)	Number of hotels in the sample	Companies registered in a city - AIDA	Hotels in the city - ISTAT
Rome	2,873,494	26,944,569	339	980	1,191
Milan	1,351,562	11,852,973	113	350	427
Venice	261,905	11,685,819	108	213	404
Florence	382,258	10,056,157	105	193	390
Naples	970,185	3,243,737	36	246	157
Turin	886,837	3,717,634	24	95	132

2.5 Findings

Table 5 shows the descriptive statistics of the sample and provides several insights into the composition of the sample.

Table 5: Descriptive statistics

No.	Variable	Mean	Std Dev	Min	Max
1	Hotels' profitability growth - Delta ROA [%]	0.037	10.488	-69.000	117.410
2	Hotels' profitability growth - Delta ROS [%]	-0.204	9.476	-51.370	55.990
3	Central Airbnb capacity usage [#]	2,732,934	1,729,826	223,489	5,183,925
4	Attractiveness of the city zone [dummy]	0.673	0.469	0	1
5	Online reputation [#]	4.157	0.354	2.300	4.900
6	Touristic flows [#]	19,014,039	8,689,877	3,243,737	27,774,461
7	Hotel capacity [#]	58.670	65.575	3	1,000
8	Hotel competition [#]	13,311.000	9,829.488	191	29,875
9	Restaurants near the hotel [#]	208.200	146.985	0	677
10	Hotel star category [#]	3.419	0.797	1	5
11	City size [#]	1,908,065	1,114,453	261,905	2,873,494
12	Age of the hotel [#]	21.870	18.805	2	100
13	Hotel business friendly [dummy]	0.362	0.481	0	1

First, the attractiveness of a city zone, which is the variable that was used to split the hotels between those in the city centre and the ones outside the city centre, shows that the 67.3% of the hotels in the sample are in the city centre, and two balanced sub-samples were therefore created. Second, the online reputation of hotels is higher than 4, thus showing a skewness of the review distribution.

The considered hotels range from a tiny three-room hotel to a vast 1,000 room structure, with some hotels having just been founded and others with a long history of up to 100 years of activity. The hotels on average have 59 rooms, have been in operation for almost 22 years and are three or four-star hotels. They on average have 208 restaurants nearby that make them attractive, and face competition from another 13,311 rooms of the same category in the city. As far as the business services offered are concerned, 36% of the hotels are business-friendly, offering services related to the business segment, while the others do not offer any service to this customer segment.

Table 6, which contains pairwise Spearman correlation coefficients with a significance level for the variables of the models, shows several significant relationships between the variables; as a first step, we looked for significant correlations higher than 0.8, since high correlations may raise concerns regarding multicollinearity in the models (I. P. Tussyadiah & Pesonen, 2016). The first significant higher correlation than 0.8 is observed for the two profitability growth variables, but since they were treated in distinct models, it was not considered as an issue for the correctness of the models. We expected a high correlation between the two variables, since both of them act as a measure of a hotel's profitability. The touristic flow variable is highly and significantly correlated with two other variables: Central Airbnb capacity usage and City size. Since the space available in touristic cities constrains both the magnitude of touristic flows and the Airbnb offer, we were not surprised by the high correlation. We excluded the risk of multicollinearity by testing the VIF levels of all the variable combinations, as described in the section regarding the models. The other correlations were all found to be below the threshold of 0.8, and they therefore did not raise any concern regarding multicollinearity. It is interesting to note the significant positive correlation between Online reputation and Attractiveness of the city zone, which means that hotels in central areas have higher scores, and the significant negative correlation between Attractiveness of the city zone and Business friendly hotel, which means that those hotels that offer services to business travellers are located more frequently outside the city centre.

Table 6: Spearman's correlation matrix

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Hotels' profitability growth - Delta ROA	1.000												
2	Hotels' profitability growth - Delta ROS	0.871*	1.000											
3	Central Airbnb capacity usage	0.093*	0.077*	1.000										
4	Attractiveness of the city zone	-0.047	-0.029	0.103*	1.000									
5	Online reputation	-0.023	-0.014	-0.097*	0.218*	1.000								
6	Touristic flows	0.105*	0.096*	0.901*	0.023	-0.125*	1.000							
7	Hotel capacity	0.054*	0.038	-0.043	-0.196*	-0.017	0.055*	1.000						
8	Hotel competition	0.047	0.033	0.608*	-0.088*	-0.075*	0.689*	0.283*	1.000					

9	Restaurants near the hotel	-0.071*	-0.058*	0.026	0.686*	0.262*	-0.032	-0.205*	-0.091*	1.000				
10	Hotel star category	0.038	0.0253	-0.034	-0.026	0.306*	0.025	0.537*	0.384*	-0.077*	1.000			
11	City size	0.076*	0.051*	0.783*	0.013	-0.167*	0.858*	0.102*	0.625*	-0.050*	0.046	1.000		
12	Age of the hotel	0.015	0.005	-0.047	0.042	-0.028	-0.034	0.266*	0.019	0.038	0.037	-0.066*	1.000	
13	Hotel business friendly	0.044	0.039	-0.077*	-0.256*	0.122*	0.001	0.584*	0.194*	-0.282*	0.508*	0.073*	0.056*	1.000

*Note: * p-value < 0.05*

2.5.1 Models

In order to verify the two hypotheses, we ran eight fixed-effect panel regression models with year-specific and hotel-specific effects to estimate the moderating effects of Attractiveness of the city zone and Online reputation on the direct effect of Central Airbnb capacity usage on the Growth of profitability of a hotel for the 2016–2018 period. We chose the panel analysis method since we wanted to consider both the time and individual dimensions (Davies & Lahiri, 1995; Greene, 2003).

We modelled the Growth of profitability of a hotel (measured with delta ROS and ROA from the previous year) of a hotel i at time t as a function of the Central Airbnb capacity usage, of the moderation effect of the two moderating variables considered in this study, as well as of the group of control variables mentioned above. We took advantage of the data panel structure and used a fixed-effects model, which can account for the time-invariant unobserved heterogeneity of a firm. We chose a fixed-effects model over a random effects specification to handle the unobserved factors, because the fixed effects model allows the unobserved firm-specific characteristics that are constant over time, such as managerial capabilities, to be taken into account. Specifically, we used fixed-effects models with a Least Square Dummy Variable estimator (LSDV) and included the dummy variables that referred to the years and the hotels' identification in the list of independent variables. The results of a Hausman specification test supported the choice of the fixed-effect model, since a random-model would lead to an inconsistent estimator (Hausman, 1978). Before running the econometric models, we tested for multicollinearity, which can be an issue in regression analysis. All the variables were found to have an acceptable variance inflation factor (VIF) value and tolerance level, and multicollinearity was therefore not regarded as an issue (Greene, 2003).

Table 7 and Table 8 show the model specifications estimated to test hypotheses H1 and H2.

Table 7: Delta ROS regression results

Dependent variable / Independent variables	Hp	Delta ROS_t	Delta ROS_t	Delta ROS_t	Delta ROS_t
Model		M1	M2	M3	M4
Direct effects					
Central Airbnb capacity usage (AU)		-53.817**	-55.360**	-57.184**	-57.327**
		(18.175)	(18.169)	(18.407)	(18.381)
Attractiveness of the city zone (AT)		45.485*	64.065**	45.261*	62.075**
		(19.900)	(22.176)	(19.892)	(22.356)
Online reputation (OR)		-8.130†	-7.961†	3.508	-0.640
		(4.431)	(4.426)	(10.899)	(11.169)
Moderating effects					
AUxAT	H1	…	25.206*	…	22.694*
			(13.355)		(13.814)
AUxOR	H2	…	…	16.480	10.393
				(14.094)	(14.558)
Control variables					
Touristic flows		65.176**	60.266**	59.660**	57.280**
		(22.586)	(22.706)	(23.073)	(23.094)
Hotel capacity		55.735†	57.695*	56.201†	57.793*
		(30.492)	(30.470)	(30.496)	(30.478)
Hotel competition		-33.670**	-31.126**	-33.109**	-31.020**
		(11.487)	(11.551)	(11.494)	(11.555)
Restaurants near the hotel		-0.428*	-0.418*	-0.430*	-0.420*
		(0.178)	(0.179)	(0.179)	(0.179)
Hotel star category		54.605**	52.625**	54.277**	52.611**
		(20.464)	(20.464)	(20.462)	(20.469)
City size		122.039	109.873	129.996	116.056
		(210.451)	(210.273)	(210.558)	(210.505)
Age of the hotel		5.990	5.669	5.979	5.696
		(5.904)	(5.599)	85.603)	(5.601)
Hotel business friendly		-361.999*	-357.271*	-367.128*	-360.947*
		(161.620)	(161.428)	(161.654)	(161.550)
Intercept		-2,605.069	-2,395.800	-2,622.000	-2,427.310
		(2,608.157)	(2,607.094)	(2,608.000)	(2,608.124)

Note: the dummy control variables related to the years and to the hotel have been omitted from the table
**** p < 0.1%, ** p < 1%, * p < 5%, † p < 10%; standard error adjusted in parenthesis.*

Table 8: Delta ROA regression results

Dependent variable / Independent variables	Hp	Delta ROA_t	Delta ROA_t	Delta ROA_t	Delta ROA_t
Model		M5	M6	M7	M8
Direct effects					

Central Airbnb capacity usage (AU)		-46.748**	-48.318**	-46.197*	-46.386*
		(18.806)	(18.801)	(19.048)	(19.020)
Attractiveness of the city zone (AT)		33.760†	52.650*	33.795†	54.610*
		(20.592)	(22.952)	(20.603)	(23.138)
Online reputation (OR)		0.262	0.434	-1.649	-6.781
		(4.585)	(4.581)	(11.273)	(11.555)
Moderating effects					
AUxAT	H1	...	25.627*	...	28.102*
			(13.822)		(14.297)
AUxOR	H2	…	…	-2.707	-10.245
				(14.587)	(15.062)
Control variables					
Touristic flows		41.343†	36.351	42.249†	39.298†
		(23.374)	(23.500)	(23.890)	(23.902)
Hotel capacity		49.957	51.949†	49.880	51.851†
		(31.556)	(31.535)	(31.575)	(31.544)
Hotel competition		-31.651**	-29.065*	-31.745**	-29.171*
		(11.887)	(11.954)	(11.904)	(11.959)
Restaurants near the hotel		-0.228	-0.217	-0.228	-0.215
		(0.185)	(0.185)	(0.185)	(0.185)
Hotel star category		58.310**	56.297**	58.365**	56.312**
		(21.178)	(21.179)	(21.191)	(21.185)
City size		11.268	-1.123*	9.942	-7.337
		(217.691)	(217.523)	(217.917)	(217.775)
Age of the hotel		-2.889	-3.212	-2.888	-3.239
		(5.799)	(5.795)	(5.802)	(5.796)
Hotel business friendly		-307.691†	-302.876†	-306.845†	-299.209†
		(167.243)	(167.055)	(167.388)	(167.188)
Intercept		-841.482	-628.447	-838.325	-595.918
		(2,697.932)	(2,697.015)	(2,699.323)	(2,698.183)

Note: the dummy control variables related to the years and to the hotel have been omitted from the table
**** p < 0.1%, ** p < 1%, * p < 5%, † p < 10%; standard error adjusted in parenthesis.*

Overall, we ran two groups of four models. The first group (from Model 1 to Model 4) had the Delta ROS as the dependent variable, while the second group (from Model 5 to Model 8) had the Delta ROA as the dependent variable. The first model of each regression group is the baseline model, where we included the direct effect of the central Airbnb capacity usage and the two moderating variables, namely the attractiveness of the city zone and the online reputation, as independent variables. The second model of the two regression groups contains all of the three direct effects mentioned above and the interaction term between central Airbnb capacity usage and the first moderating variable, namely the attractiveness of the city zone. The third model instead contains all of the three direct effects mentioned above and the interaction term between central Airbnb capacity usage and the second moderating variable, namely the online reputation. To be able to control for both of the interaction effects, the fourth model of each regression group includes both of the interaction terms under analysis.

Model 1 and Model 5 support the results of the majority of previous research on the direct effect of Airbnb capacity usage on the performance of hotels. We found that central Airbnb capacity usage has a negative but significant impact on the sales and asset profitability growth of a hotel (Delta ROS and Delta ROA, respectively). This result shows that Airbnb has a detrimental effect on the economic performances of hotels. These models also show that the online reputation of hotels has less impact on the economic returns of hotels. These findings highlight that hotels located in an attractive city zone are those that achieve higher growth in profitability indexes, since travellers show more will- ingness to pay for a hotel close to the points of interest in a city (e.g. museums, interesting architecture) and to the local transportation systems.

In Hypothesis H1, we postulated that the attractiveness of the city zone where a hotel is located positively moderates the effect that the central Airbnb capacity usage has on the profitability growth of a hotel, with hotels located outside the most attractive zones suffering the most. Models 2 and 6 support this hypothesis, as they show a positive and significant interaction effect between central Airbnb capacity usage and attractiveness of the city zone where the hotel is located on both the return on sales and the return on asset growth. In order to obtain further support for Hypothesis H1, we traced 2-way linear interaction graphs to illustrate the moderating effect of the attractiveness of the city zone for both the return on sales and the return on asset growth. Figure 5 shows that when a hotel is located in the city centre, where the attractiveness of the city zone is higher, the negative effect of central Airbnb capacity usage on the profitability growth of a hotel is reduced. In other words, the graphs show the different impacts of Airbnb on hotels in the city centre and outside this zone. It can in fact be observed that the slope of the segment related to the hotels in the city centre is less steep, which means that high central Airbnb capacity usage has a much more substantial impact on the other categories of hotels. This holds for both the return on sales and the return on asset growth, which are affected in a very similar way by the moderating variable, thus supporting Hypothesis 1.

a) b)

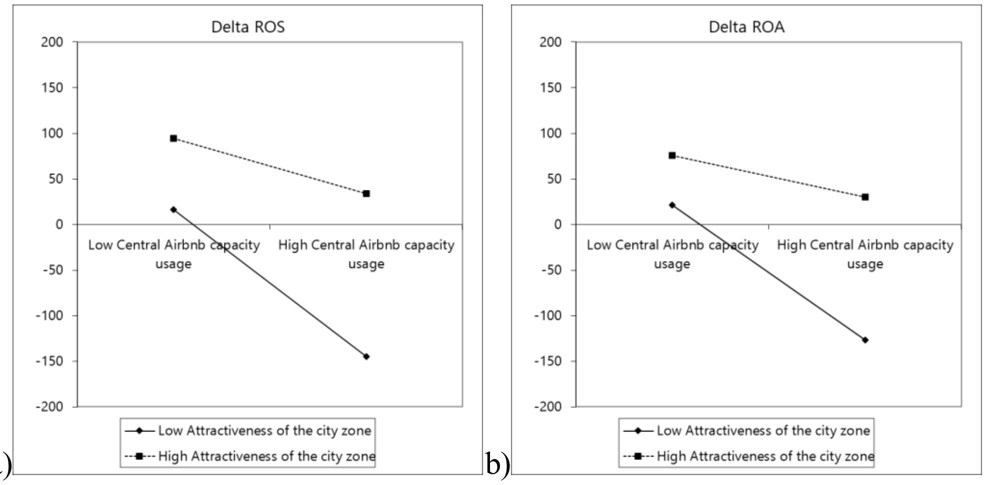

Figure 5: Interaction effect obtained when using ROS as a dependent variable (2a) and ROA as a dependent variable (2b)

In Hypothesis H2, we posited that the online reputation of a hotel is able to moderate the effect that central Airbnb capacity usage has on the growth in profitability of such a hotel. However, this hypothesis has not been supported by any empirical data. Models 3 and 7 include the interaction term between the Trustyou score and profitability indexes of hotels, which is not significant.

There could be various reasons why this result does not support Hypothesis 2. First, the capabilities needed to respond to the disruptive innovation introduced by the home-sharing platforms may have to do with radical innovation (Christensen & Raynor, 2003; Karimi & Walter, 2015) and with what Teece (2014) indicated as 'dynamic capabilities', namely 'higher-level activities that can enable an enterprise to direct its ordinary activities towards high-payoff endeavours' (Teece, 2014). This idea is based on the tenet in the disruptive innovation theory that well-established companies are able to resist and survive the entrance of a disrupter into their market when they can enact innovation endeavours which, at the same time, do not increase their cost position and can serve more sophisticated and complex customer needs, thereby providing higher benefits to customers (Christensen, 1997). By developing their view on blue ocean strategies, Chan et al. (2005) reinterpreted such a tenet by contending that firms are successful when they redesign their products/services and they focus their value proposition on specific behavioural patterns of market segments that are easily identifiable with the classic market segmentation approaches (Chan Kim & Mauborgne, 2005). Such a service redesign includes raising or creating features that increase a buyers' willingness to pay, and reducing and eliminating the features customers do not associate particular benefits with and which worsen the firms' cost position. The above-mentioned effort of the Marriott chain to offer hybrid home-sharing logics goes in this direction, as does the attempt of hotels to compete on memorable experiences. Frei (2006) showed that excellence in this aspect can be achieved by asking customers to do part of the work that is usually done by the service provider (Frei, 2006). These arguments lead to contend that the ordinary capabilities reflected on the online reputation expressed by travellers may not reflect such a capability of hotels to redesign their service levels in new ways that could contrast the diffusion of the service offered by disruptors.

Second, it has been reported, in the recent literature, that reviews are currently skewed towards the higher part of the rating scale, thereby reducing the discriminating power when tourists make their choices (Schoenmueller et al., 2018). Because of this evidence, we investigated and found confirmation of this aspect in our data (Figure 6).

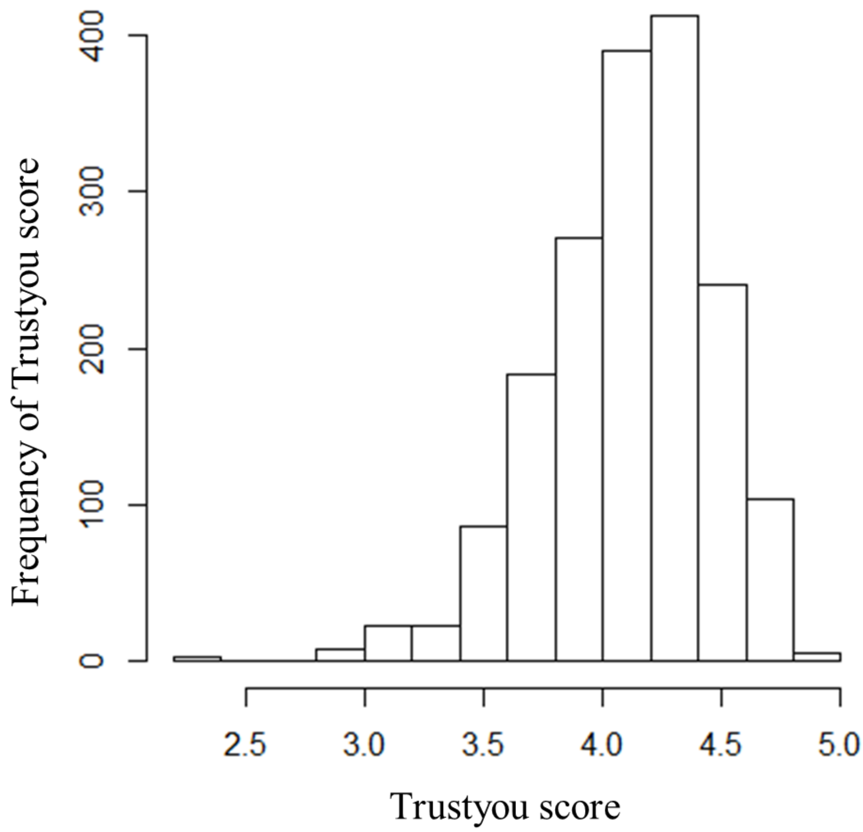

Figure 6: Distribution of reviews in the sample

We also ran Model 4 and Model 8 to validate hypotheses H1 and H2, simultaneously. Since the interaction effect between central Airbnb capacity usage and the attractiveness of the city zone where a hotel is located is positive and statistically significant, and since the interaction effect between central Airbnb capacity usage and the online reputation is not significant in any of these models, it is possible to assert that they validate the results of the previous models.

2.5.2 Post-hoc analysis

In order to further explore the meaning of the non-significant interaction term between online reputation and central Airbnb capacity usage, we performed a sensitivity analysis to assess whether an extreme positive online reputation, as represented by very high values of online reputation, could have a moderating effect on the negative effect of Airbnb on the growth of profitability of hotels that the previous analyses were not able to catch. We therefore created a dummy variable that split the sample into hotels with a high reputation and hotels with a low reputation. The threshold value, which was very close to the average value, started at 4.1 and was then increased by steps of 0.2 until a maximum value of 4.9 was reached, in order to evaluate whether an extremely high online reputation could help hotels to face disruption. The used models are the same as the ones used in the previous analysis, with the only difference being that the online reputation was operationalized as a dummy variable. The results of this analysis are shown in Table 9 and Table 10. The results are coherent with the results of the previous analysis, since the interaction effect between online reputation and the Airbnb variable is still not significant for any of the five thresholds tested.

In conclusion, the result of this post-hoc analysis is coherent with the result regarding H2, and it reinforces the lack of the moderating effect of online reputation, even in the case of an extreme online reputation.

Table 9: Robustness check – Delta ROS

Dependent variable **Independent variables**	**Delta ROS_t**	**Delta ROS_t**	**Delta ROS_t**	**Delta ROS_t**	**Delta ROS_t**
Threshold value	High ≥ 4.1	High ≥ 4.3	High ≥ 4.5	High ≥ 4.7	High ≥ 4.9
Direct effects					
Central Airbnb capacity usage (AU)	-56.662**	-56.992**	-56.363**	-56.082**	-56.167**
	(18.080)	(18.077)	(18.078)	(18.086)	(18.087)
Attractiveness of the city zone (AT)	48.585*	49.419*	48.500*	49.696*	48.694*
	(21.522)	(21.546)	(21.549)	(21.535)	(21.548)
High online reputation – dummy variable (HOR)	0.545	0.720	0.267	-0.432	0.012
	(0.529)	(0.560)	(0.592)	(0.489)	(0.476)

Moderating effect					
AUxHOR	0.528	-0.0732	0.379	-0.230	0.450
	(0.511)	(0.540)	(0.563)	(0.477)	(0.474)
Control variables					
Touristic flows	64.493**	65.234**	64.357**	64.438**	64.703**
	(22.257)	(22.276)	(22.272)	(22.392)	(22.263)
Hotel capacity	54.655†	56.112†	52.663†	55.620†	54.841†
	(31.316)	(31.349)	(31.556)	(31.369)	(31.333)
Hotel competition	-32.208**	-33.136**	-32.187**	-32.974**	-32.639**
	(11.527)	(11.515)	(11.543)	(11.501)	(11.504)
Restaurants near the hotel	-0.418*	-0.422*	-0.423*	-0.433*	-0.418*
	(0.181)	(0.181)	(0.182)	(0.183)	(0.181)
Hotel star category	50.201*	51.573*	50.085*	51.251*	50.815*
	(20.264)	(20.258)	(20.300)	(20.247)	(20.249)
City size	46.946	59.021	44.017	50.413	44.136
	(209.089)	(209.781)	(209.381)	(209.355)	(209.478)
Age of the hotel	4.696	4.597	4.745	5.081	4.646
	(5.420)	(5.423)	(5.435)	(5.430)	(5.427)
Hotel business friendly	-336.692*	-347.878*	-332.633*	-346.129*	338.034*
	(166.013)	(166.239)	(166.447)	(166.043)	(166.085)
Intercept	-1651.178	-1814.829	-1605.268	-1690.849	-1617.736
	(2592.282)	(2600.283)	(2595.951)	(2597.333)	(2595.548)

Note: the dummy control variables related to the years and to the hotel have been omitted from the table

**** p < 0.1%, ** p < 1%, * p < 5%, † p < 10%; standard error adjusted in parenthesis.*

Table 10: Robustness check – Delta ROA

Dependent variable **Independent variables**	**Delta ROA$_t$**	**Delta ROA$_t$**	**Delta ROA$_t$**	**Delta ROA$_t$**	**Delta ROA$_t$**
Threshold value	High ≥ 4.1	High ≥ 4.3	High ≥ 4.5	High ≥ 4.7	High ≥ 4.9
Direct effects					
Central Airbnb capacity usage (AU)	-51.475**	-51.514**	-50.820**	-50.971**	-51.023**
	(18.696)	(18.645)	(18.687)	(18.712)	(18.707)
Attractiveness of the city zone (AT)	33.549	34.242†	33.097	33.407	33.304
	(22.263)	(22.235)	(22.283)	(22.288)	(22.272)
High online reputation – dummy variable (HOR)	0.700	1.233*	0.213	0.050	0.337
	(0.548)	(0.579)	(0.612)	(0.506)	(0.492)
Moderating effect					
AUxHOR	0.248	-0.030	0.272	0.013	0.227
	(0.529)	(0.557)	(0.583)	(0.494)	(0.490)
Control variables					
Touristic flows	44.377†	44.848†	43.966†	44.160†	43.863†

	(23.023)	(22.988)	(23.030)	(23.174)	(23.035)
Hotel capacity	49.681	51.001	49.124	49.584	49.395
	(32.397)	(32.361)	(32.633)	(32.467)	(32.415)
Hotel competition	-31.693**	-32.164**	-31.741**	-31.772**	-31.814**
	(11.927)	(11.884)	(11.939)	(11.906)	(11.907)
Restaurants near the hotel	-0.228	-0.231	-0.224	-0.226	-0.226
	(0.188)	(0.187)	(0.188)	(0.189)	(0.188)
Hotel star category	58.338**	59.030**	58.382**	58.456**	58.521**
	(20.967)	(20.906)	(20.996)	(20.960)	(20.948)
City size	-54.880	-38.276	-57.237	-56.956	-54.944
	(216.250)	(216.447)	(216.473)	(216.631)	(216.538)
Age of the hotel	-2.867	-3.117	-3.143	-2.963	-3.066
	(5.600)	(5.592)	(5.613)	(5.613)	(5.606)
Business-friendly hotel	-280.353†	-289.823†	-277.782†	-279.419	-279.953†
	(171.792)	(171.580)	(172.117)	(171.845)	(171.791)
Intercept	-68.299	-284.415	-29.409	-37.639	-56.893
	(2680.997)	(2684.186)	(2683.824)	(2687.547)	(2683.926)

Note: the dummy control variables related to the years and to the hotel have been omitted from the table

**** p < 0.1%, ** p < 1%, * p < 5%, † p < 10%; standard error adjusted in parenthesis.*

2.6 Discussion and conclusion

This study adopts a lens that is based on the disruptive innovation theory (Christensen, 1997) to investigate the effect of the diffusion of the leading sharing accommodation platform – Airbnb – on the profitability growth of independent hotels located in the vicinity of a hotel. We have focused on two essential properties of the portfolio of resources and capabilities that hotels can deploy to cope with the disruption exerted by new entrants, such as Airbnb. Such factors are the tourist attractiveness of the micro-zone in which a hotel is located and the extent of its ordinary capabilities, as reflected in the reviews generated by travellers on infomediary platforms. These two factors reflect ‘what to sell and where to locate’ (Baum & Haveman, 1997; Sainaghi, 2011), and they have been highlighted, under a situation of environmental stability, as being critical for the performance of a hotel and for its capability to survive in the long-term (Litvin et al., 2008; Ziqiong Zhang et al., 2011). We focused on this topic since the recent literature (Blal et al., 2018; Dogru et al., 2019; Zervas et al., 2017) has still not been able to disentangle all the complex relationships that can moderate the direct substitution effect. Accordingly, we tested whether these two factors mitigate the competitive threats to profitability posed by disruptors, and whether these factors allow hotels to survive and prosper in times of disruption. Overall, the findings of this study contribute to the literature by adding evidence to the on-going debate about how the tourism sector is changing and how incumbents can react to new entrants.

2.6.1 Theoretical contribution

This study contributes to the emerging literature debate on the economic impacts of the sharing economy on the incumbent hotel industry. Adopting a lens based on the disruptive innovation theory (Christensen & Raynor, 2003), we support, with empirical evidence, the application of the theory to the rise in sharing economy short-term rental platforms.

It has already been analysed, in the literature, how the rise in sharing economy platforms in the hospitality service industry has affected the performance of hotels (Blal et al., 2018; Dogru et al., 2019; Zervas et al., 2017), but mixed results have been found, thus limiting the understanding of the circumstances under which hotels suffer the least from the disruption effects that sharing economy schemes introduce into this industry. Given these mixed results, and given the absence of studies that have investigated the capability of hotels to cope with the competitive threats exerted by such disruptors as home-sharing platforms, we contribute to the literature on disruptive innovation in the tourism context by investigating two essential properties of the portfolio of resources and capabilities that hotels can deploy to protect their competitive advantage from a substitute product offered by the disruptor. We have provided evidence that the first critical factor, that is, the attractiveness of the micro-zone where the hotel is located, allows incumbents to manage the disruption introduced by accommodation sharing platforms. In fact, since the central location of a hotel is a valuable resource that is challenging to imitate, and almost unique, due to the scarcity of free space in city centres, we see it as a Ricardian rent, which is able to grant a performance advantage over hotels outside the attractive zone. The Ricardian rent also depends on the fact that a hotel located in the city centre has the advantage of being more favourably located in an ecosystem with several points of interest, museums, restaurants, etc., which in turn provide additional opportunities and performance advantages to hotels.

We have also found that the second critical factor, that is, the extent of a hotel's ordinary capabilities, as reflected in the reviews generated by travellers on infomediary platforms, is not a significant factor in protecting the incumbents in the analysed context from the disrupters. We reinforced this evidence also with the post-hoc analysis where we considered the moderating role of extremely positive reviews. Such a result may suggest that hotels need to develop the capabilities that have to do with radical innovation, and which have been defined as ‘dynamic capabilities’ in the literature (Teece, 2007), to respond timely and effectively to the business model innovations introduced by home-sharing platforms.

2.6.2 Managerial implications

From a managerial point of view, some implications may be derived from our study. First, we support the point that underestimating sharing economy platforms may result in a significant threat in the future, since they first started focusing on low-value customers. Plans to counteract this threat should be deployed, and all the interested parties should be aware of the potential magnitude of the threat, which has been evolving quickly. For example, two of the factors that the literature has pointed out as being necessary to protect hotels are the services offered to the business customer segment and those for the high-end market, even though both of these factors are now explicitly targeted by Airbnb, which has developed the ‘Airbnb plus’ feature for high-end travellers (https://www.airbnb.co.uk/plus) and ‘Airbnb for work’ for business travellers (https://www.airbnb. co.uk/work?).

Second, this study informs managers about the fact that the location of a hotel is currently a salient variable that allows the hotel to recover from the disruption effects exerted by sharing economy schemes, whereas the ordinary capabilities that result in a high online reputation have no particular effects in this direction. In other words, our results indicate that within an urban context, the hotels outside the centres are the ones that need to reinvent their business model the most. Moreover, we suggest that independent hotel managers should take advantage of the knowledge they can derive from the innovative processes large hotel chains introduce. We in particular suggest focusing on creating alliances and/or networks with entities from other sectors, as large tourism firms are currently doing (Pikkemaat & Peters, 2006; Weiermair, 2006). These long-term mutual beneficial alliances/networks can have a positive effect on both costs and revenues, since the traditional production factors in tourism have to share their relevance even more with other ‘tourism structure and supra-structures’ (Pine II & Gilmore, 1998; Wolf, 1999).

2.6.3 Limitations and future research

Although this study provides a research contribution to the circumstances under which hotels are protected from the disruption and substitution effect exerted by the diffusion of Airbnb, it suffers from some limitations that may be addressed in future research.

First, we have applied the disruptive innovation theory to a different context from the one for which it was originally considered. The main difference has to do with the fact that the disruptive innovation theory was initially developed for market contexts in which customer choices were oriented by objective elements related to how technology affected the performance of a product, while the characteristics of tourism services, such as hedonic goods, make emotions a factor that plays an essential role in the purchasing process.

Second, future studies could investigate the existence of other moderating effects in the relationship between the sharing economy and the growth in profitability of hotels in order to understand the conditions that allow managers to achieve less negative results, given the presence of Airbnb as a substitute product. From this point of view, our attention to the role of ordinary capabilities paves the way to taking into consideration how hotels can build dynamic capabilities (Teece, 2014). Christensen's theory would seem to suggest that incumbents have to reinvent their product in order to increase the benefits for customers in upmarket segments, albeit without excessively increasing costs. In the hospitality industry, this has probably to do with how hotels are capable of redesigning their services and business models in new ways, while taking advantage of the opportunities available in the technology environment and in the ecosystem represented by touristic services. This process of sensing and seizing opportunities (Teece, 2007) calls for studies to analyse how hotels can build dynamic capabilities to cope with the change in the industry introduced by home-sharing platforms.

Third, the study is based on a specific hotel subset (independent hotels) located in the six most attractive historical cities for national and international tourism in Italy. Accordingly, these findings cannot be generalized to settings with different touristic drivers. Further research could replicate the study in different settings, in order to understand how differences in the supply and demand conditions, due to the nature of the cities, affect the generalisability of the findings.

Chapter 3

The impact of Airbnb on rural touristic destinations

3.1 Introduction

Sharing economy platforms are deeply transforming the way people interact with each other and make business. Everyone can witness this change, nowadays most of goods and services are available with few taps of our fingertips, also thanks to the matchmaking mechanism of digital sharing economy platforms.

Among the industries where this transformation is happening the tourism ecosystem is for sure one of the most affected (Frenken & Schor, 2017; Hamari et al., 2015; Marios Sotiriadis, 2017; I. P. Tussyadiah & Pesonen, 2016), due to the tangible usefulness of the matchmaking mechanism in finding the right offer for the right demand (Guttentag & Smith, 2017) and the abundance of under-utilized assets to be offered on the platforms (Marios Sotiriadis, 2017). In the literature it is possible to find many researches highlighting the disruptive effects of sharing economy accommodation platforms growth on touristic ecosystem in well-known destination (Blal et al., 2018; Choi et al., 2015; Destefanis et al., 2020; Dogru et al., 2019, 2020; Zervas et al., 2017). In this context phenomena such as airification and gentrification of city centres take place (Diaz-Parra & Jover, 2020; González-Pérez, 2020; Wachsmuth & Weisler, 2018). But, if on one hand, destinations already popular may experience the negative side of democratising the accommodation supply, on the other hand in less popular destinations sharing economy accommodation platforms may act as an economic flywheel for local communities (Battino & Lampreu, 2019; Strømmen-Bakhtiar et al., 2020; I. P. Tussyadiah & Pesonen, 2016). In fact, lowering and distributing among lots of micro-entrepreneurs the investment needed to the creation of touristic accommodation, the sharing economy accommodation platforms make possible to valorise wanna-be touristic destinations with touristic assets without the need of concentrated big investments from external players (Ditta-Apichai, Kattiyapornpong, & Gretzel, 2020; Katsinas, 2021; Petrou, Pantziou, Dimara, & Skuras, 2007). Moreover, sharing economy accommodation platforms work as digital showcase, helping these communities not only to build the accommodation offer but also to present it to the public of potential customers (Aleksandrov & Fedorova, 2018). The contents of this chapter have been taken from a working paper with the title "Estimating the impact of sharing economy accommodation platforms on rural tourism ecosystems: an empirical investigation in Italian "Borghi".

3.2 Literature review

Rural touristic destinations represent an optimal setting to explore this mechanism of economic flywheel introduced in previous paragraph and previous literature specifically calls for contribution in touristic rural entrepreneurship (Fu et al., 2019). Rural tourism is often indicated as a mean to improve local economy and to create jobs (Pröbstl-Haider, 2010; Pröbstl-Haider et al., 2014), but the poor infrastructures characterizing by definition rural territories means most of them are not included in the popular touristic destinations, since the infrastructures needed to reach touristic destinations are among the most important tourism related success factors (Denicolai et al., 2010). The rise of a different kind of travellers, interested in exploring and experiencing less popular and reachable destinations, and the explosion of internet for everybody made possible for those travellers to discover a new set of potential destinations thanks to the power of eWOM (electronic Word Of Mouth) and accommodation platforms (I. P. Tussyadiah & Pesonen, 2016).

Past literature has already suggested that short term accommodation platforms like Airbnb act as a mean to increase tourism in less developed destinations. In Lofoten Islands, Norway, Strømmen-Bakhtiar et al. (2020) highlight the role Airbnb had in rising local tourism, stimulating the conservation/restoration of traditional houses and increasing recreational mobility for the inhabitants. Battino & Lampreu (2019) state that sharing economy is a helpful model to reduce or even stop depopulation of rural areas of Sardinia region, Italy. The research proposes sharing economy based models as an ally to fight unstable economic situation and social exclusion, that are the main causes of depopulation of rural territories, so, rural destinations actively working to increase well-being of inhabitants should consider this option. Johnson & Neuhofer (2017) even suggest that the way Airbnb is made is able to push the co-creation of value for the destination community through the interaction between hosts and guests, that generate unique experiences for both. Finally, Aleksandrov & Fedorova (2018) focus on rural North-western federal districts of Russian federation, recognizing the importance of digital sharing economy business models to boost local economies.

3.2.1 The research gap

At the best of our knowledge there is a gap in the literature regarding the quantitative effects of such players' growth in less popular and smaller touristic destinations, since previous works are based on qualitative methodologies and try to propose conceptual framework. Given the gap in the literature, the timeliness of the phenomenon and the importance for rural destination to better understand possible factors enhancing local tourism ecosystem we aim at answering the following research question: *"Can sharing economy accommodation platforms act as an economic flywheel for rural touristic destination?"*

3.3 Hypotheses development

3.3.1 Theoretical background

The framework we adopted to answer the research question is based on the Resource Based View (RBV) theory (Wernerfelt, 1984) as used to explain entrepreneurial dynamicity in areas with low tourism relevance (Denicolai et al., 2010). RBV suggests that the wise combination of assets of the firm (tangible, intangible and human) is the key for the generation of capabilities by employees and organizational units (Wernerfelt, 1984). Denicolai et al. (2010) propose to apply RBV theory to territories and touristic destinations, since they are characterised by the presence of multiple independent agents mutually interdependent on each other, part of the same system, and seen as a unique system by the travellers/customers. In fact, in tourism ecosystem, the different agents depend on each other in order to successfully attract and satisfy tourists that feed local economy, since the latter evaluate the entire experience of staying in a destination before to suggest or advise against that (Buhalis & Spada, 2000).

Denicolai, Cioccarelli & Zucchella (2010) identify four primary elements of tourism value network, that are accommodation facilities, places to eat, event and resources and finally the infrastructure. The authors also highlight the fundamental role of intermediaries to attract tourists. These elements composing the tourism offer are deeply related to each other, to the point that they are defined as a value constellation, vertically, horizontally and diagonally integrated (Denicolai et al., 2010; Weiermair, 2008).

As a consequence, the tourism destination competes as a single inter-firm network configuration, and even the lack of a single touristic resource/asset represents a strong obstacle in achieving competitive advantage.

3.3.2 Hypotheses

Given the theoretical background described in the previous chapter we wonder whether technological innovation could help rural destinations to attract more tourists. More specifically, we explored the role of Airbnb and the moderation effect coming from online visibility.

Sharing economy platforms like Airbnb act as intermediaries but also ease the process of building accommodation facilities, making it possible also for local micro-entrepreneurs (Dann, Teubner, & Weinhardt, 2019; Ditta-Apichai et al., 2020; Teubner, Hawlitschek, & Dann, 2017). On top of that public administrations of rural communities can empower their micro-entrepreneurs by improving the online visibility of the municipality. Online visibility is a variable commonly defined as an indicator of the success of entities because it allows customers to know the services offered before making the purchasing decision (Lahuerta Otero, Muñoz Gallego, & Pratt, 2014; Melo, Hernández-maestro, & Muñoz-gallego, 2016; Smithson, Devece, & Lapiedra, 2011; Teodoro, Dinis, Simões, & Gomes, 2017).

We propose three mechanisms supporting our hypotheses: the first way Airbnb is able to improve touristic income is by easing the creation of accommodation. Group of micro-entrepreneurs can dedicate a number of small structures to hosting traveller as an alternative to a single big investments to create a single structure (Ditta-Apichai et al., 2020), lowering the risk and the resources needed.

Second, Airbnb is an intermediary, and it is able to show to unaware potential customers some destinations they couldn't have discovered in other ways. Since the target of the current analysis are small, traditionally less touristic places, they can only get advantage by being put on a map showed to travellers.

Third, Airbnb acts as a facilitator of networking among experienced and new hosts, favouring the spill-over of competencies towards less popular destinations, it aims at creating involvement in the community (Panyik, Costa, & Rátz, 2011) and it contributes to the process of hosts professionalization (Katsinas, 2021).

Given the premises we wonder whether Airbnb listing and usage growth is actually linked with touristic flows increase. Therefore, we hypothesize the following:

HP3 "Airbnb supply increases the touristic flows of the rural destination"

On top of that we also wonder whether the online presence of local communities can moderate HP1 reinforcing the role of Airbnb supply, therefore we hypothesize the following:

HP4 "Online visibility, measured by the presence of destination's institutional and touristic websites, positively moderates the relation between Airbnb supply and the touristic flows of the rural destination"

3.4 Methodology

In order to answer to the hypotheses, we performed an empirical analysis on a coherent context of analysis. In our research we took as a proxy of the total sharing economy accommodation platforms diffusion the data coming from Airbnb. Airbnb is the most successful accommodation platform worldwide and the core of its business is represented by European and US touristic regions, so it represents very well the behaviour of the overall sharing economy accommodation platforms in Italy, that is the country where the analysis has been carried out. More specifically the analysis takes into consideration the 308 villages ("borghi") part of the association "I borghi più belli d'Italia" (the most beautiful villages of Italy). The borghi must respect some criteria about the size and the touristic interest to be part of the association, making them perfect to answer to the research questions. All the villages have been studied and we collected several characteristics of each one of them from 2016 to 2019. Fixed effect panel regression models have been used to support the hypotheses, controlling for year effects using STATA 14.0 software. Before running these models, a Hausman specification test will be run for each of them to establish the appropriateness of a fixed effect model over a random effect model, as the estimates from the random effect model were not consistent. We expect that models confirm our hypotheses.

3.4.1 Measures

Dependent variable

Touristic arrivals. The dependent variable is represented by the arrivals in the destination during the year. The variable is obtained from ISTAT, the Italian National Institute of Statistics (www. istat.it).

Independent variable

Airbnb supply. This construct refers to the total number of Airbnb room-nights available in a year in the destination level (Dogru et al., 2019; Zervas et al., 2017). The variable is computed from a proprietary database built on AirDNA data (https://www.airdna.co/). This variable was normalized to compute its interaction effect with the two moderating variables.

Moderating variables

Institutional website. The variable was operationalized through a Boolean indicator describing the presence or not of an institutional website of the destination. The online visibility of a touristic attraction, representing the possibility of being found online, is important for any entity in tourism ecosystem (Melo et al., 2016; Smithson et al., 2011). This variable was normalized to compute its interaction effect.

Touristic website. The variable was operationalized through a Boolean indicator describing the presence or not of an official website explicitly dedicated to the tourism of the destination. As mentioned in the previous paragraph, online visibility is important (Melo et al., 2016; Smithson et al., 2011), we also aimed at capturing the effect of an additional effort to develop online visibility as a touristic destination. This variable was normalized to compute its interaction effect.

Control variables

Airport distance. The variable measures the distance in kilometers of the destination to the nearest airport. The variable aims at capturing the infrastructure proximity to the destination, since it could influence its touristic performance (Denicolai et al., 2010; World Economic Forum, 2017).

Natural resources. The variable was operationalized through a Boolean indicator describing the presence or not of natural resources in the destination. Natural resources (lakes, rivers and parks) are important assets to attract tourism, since they can provide memorable experiences to the visitors (Denicolai et al., 2010; Strømmen-Bakhtiar et al., 2020).

UNESCO heritage site. The variable was operationalized through a Boolean indicator describing the presence or not of an UNESCO heritage site in the destination. UNESCO selects the attractions to include in the list certifying their value to the public and giving them even more visibility, increasing the value represented for the community (Brzezińska-Wójcik & Skowronek, 2020; Denicolai et al., 2010).

Hotels. The variable measures the number of hotels in the destination. This number controls for the touristic development of the destination. Hotels usually compete with Airbnb (Becerra et al., 2013) but in the case of less popular touristic destinations their presence together with Airbnb offer could reinforce the destination attractiveness.

Surface. Finally we included the squared kilometres of surface of the destination as a measure its size, to make easier the comparison among different destinations (Piccoli, 2008).

3.5 Results

In order to verify the formulated hypotheses, we ran 3 fixed-effect panel regression models with year-specific and hotel-specific effects to estimate the direct result of Airbnb supply growth on touristic arrivals and the moderation coming from the presence of the website.

Table 11: Regression results

Dependent variable **Independent variables**	**HP**	**Touristic arrivals**	**Touristic arrivals**	**Touristic arrivals**
Model		**M1**	**M2**	**M3**
Direct effects				
Airbnb supply (AS)	H3	4,262***	4,419***	4,041***
		(-324.9)	(-331.2)	(-334.6)
Institutional website (IW)		-5,552***	-5,551***	-5,572***
		(-1616)	(-1596)	(-1596)
Touristic website (TW)		923	899.2	887.3
		(-1554)	(-1534)	(-1534)
Moderating effects				
AS x IW	H4	…	525.7**	…
			(-240.2)	
AS x TW	H4	…	…	872.8***
				(-303.6)
Control variables				
Airport distance		-53.49	-53.92	-54.44

	(-47.58)	(-46.96)	(-46.97)
Natural resources	1,573	1,538	1,511
	(-1350)	(-1332)	(-1333)
UNESCO heritage site	9,585**	9,265*	9,029*
	(-4801)	(-4741)	(-4743)
Hotels	5,181***	5,279***	5,242***
	(-471.3)	(-468.5)	(-467.6)
Surface	14.45	14.54	14.02
	(-29.18)	(-28.8)	(-28.8)
Intercept	12,498***	12,591***	12,666***
	(-3792)	(-3743)	(-3744)

Note: the dummy control variables related to the years and to the hotel have been omitted from the table.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; standard error adjusted in parenthesis.

In the column of the model 1 of Table 11 it is possible to see that HP3 is supported with a positive and significant correlation coefficient. Considering the control variables, the presence of hotels in the territory is also positively and significantly correlated with the touristic arrivals in the three models, since hotels also provide accommodation facilities to the tourists. Moreover, the presence of UNESCO heritage sites also is positively and significantly correlated to the touristic arrivals in the three models; this fact supports even more the role of resources and visibility in enabling tourism in a destination (Denicolai et al., 2010).

Moving to the columns of model 2 and model 3 is possible to note that HP4 is also supported, since the moderation coefficients of the presence of institutional website and official tourism portal crossed with Airbnb supply are positive and significant.

3.6 Conclusion

Overall, this research contributes to the emerging literature debate on the socio-economic impacts of sharing economy on small, rural touristic destinations. From a theoretical standpoint the study points out how in tourism ecosystem the nodes of the value networks are strongly interconnected and how they depend on each other. From a managerial perspective it shows to micro-entrepreneurs that their role is fundamental in valorising touristic assets of their community, and how sharing economy accommodation platforms allow them to easily generate accommodation facilities, behaving as a pull for complementary touristic activities and for tourism flows. Specifically, we propose three contributes coming from Airbnb: creating accommodation (by reducing risk and cost), acting as intermediary to the public (letting them know the destination, with specific effort to valorise borghi) and facilitating networking among experienced and new hosts and community.

On the other side the research recognizes the value generated by the online visibility coming from the presence of official websites describing the territory, as part of the effort needed from a public administration to become more attractive from a touristic perspective.

3.6.1 Limitations and future research

This paper, even proposing interesting contribution about the role of sharing economy accommodation platforms in touristic flow generation for less popular destinations, is limited in some aspects that should be developed in future research.

First, the focus is on Italian rural destinations, differences may emerge analysing other territories, subject to other regulation and cultural factors. Future studies should focus on different countries in order to compare the effect witnessed here.

Second, future research should go more in depth in the consequences caused by the increased number of tourists in the destination, are those territories able to capture the additional value? Where does the line between the positive and the negative impact on communities lie, if it could be drawn?

We believe this research and these research proposals will help communities to better understand the controversial topic of the tourism impact on rural destination and the role of digital platforms, allowing regulators to make the best decisions for our society as a whole.

Chapter 4

Artificial intelligence diffusion in tourism industry

4.1 Introduction

The emergence of artificial intelligence (AI) in the early twenty-first century has triggered a discussion about its role in several sectors of the economy and society. AI is one of the most promising technologies of our time, which has developed dramatically due to the enhanced processing capacity of computers and the accumulation of data (Lu, Li, Chen, Kim, & Serikawa, 2018). Nowadays, AI machines can perform intellectual activities that only human workers could complete Coombs et al. (2021) and are already being used widely in many industries, including manufacturing, supply chain, health care and retailing (Leone, Schiavone, Appio, & Chiao, 2020). The AI software market is lucrative, with an average global growth rate year-on-year of 38% from US$22bn in 2020 (Tractica, 2019).

Amongst the others, AI is considered one of the potentially most revolutionary and innovative technologies in the tourism industry (Ivanov & Webster, 2019b). AI can contribute to a new digital transformation (Murphy et al., 2017), changing structures, practices and how firms collaborate and create value (K. Xie et al., 2016), representing a major technological shift Brynjolfsson and McAfee (2014) that will affect consumer behaviour and impact on the industry structure in the near future. Although there is a growing interest in AI and the implementation of service robots in the travel and tourism industry (TTI), existing scholarly works are mainly conceptual. For instance, scholars have focussed on the potential benefits and risks deriving from the implementation of intelligent robotic technology in the hospitality sector (Buhalis et al., 2019; Ivanov & Webster, 2019b; Murphy et al., 2017; Samara, Magnisalis, & Peristeras, 2020; Tung & Au, 2018; Tung & Law, 2017; I. Tussyadiah, 2020). Empirical research has looked at consumers' perceptions of service robots and their hypothetical interaction and response to encounters with them (Belanche, Casaló, & Flavián, 2020; Belanche, Casaló, Flavián, & Schepers, 2020b; de Kervenoael, Hasan, Schwob, & Goh, 2020; Mende, Scott, van Doorn, Grewal, & Shanks, 2019; I. P. Tussyadiah & Park, 2018; Yu, 2020).

However, no study has focussed on AI-based entrepreneurial activities. The study of digital entrepreneurship is in its infancy in the tourism industry and the entrepreneurship and innovation literature (Nambisan, 2016; Obschonka & Audretsch, 2020). Scholars call for more empirical works on AI, big data and entrepreneurship; specifically, they call for more research to identify and predict entrepreneurial characteristics and performance outcomes of people, teams and organisations (Obschonka & Audretsch, 2020). Given these research gaps, this study focusses on start-ups developing AI solutions for the tourism sector. According to entrepreneurship scholars, start-ups play a critical role in enhancing disruptive innovation (Markides, 2006; Solvoll, Alsos, & Bulanova, 2015), and they are the channels through which innovations are brought into a specific industrial sector by established companies (Groen et al., 2008; Markides, 2006; Walsh, 2004). Nevertheless, very little is known about the internal characteristics of successful tourism start-ups. Previous studies reveal that internal factors, such as demographic variables, are relevant for predicting the success of a new venture (Hallak, Assaker, & Lee, 2015). Under this context, we explore the characteristics of Venture Capitalists (VC)-backed AI start-ups. VC-backing can explain a start-up's superior performance (Arthurs & Busenitz, 2006), furthermore, VC-backed start-ups demonstrate better dynamic capabilities and resources for product development (Arthurs & Busenitz, 2006).

This study also looks at the AI technological domains that have received more funding from VCs to forecast how AI could shape the tourism industry. AI include various technological domains such as Reasoning, Planning, Learning, Communication, Perception, Integration and Interaction, Services, Ethics and Philosophy (Table 13) (Samoili, López Cobo, Gómez, E., De Prato, Martínez-Plumed, & Delipetrev, 2020). Research on AI in tourism is still based on descriptions of current applications and potential future implementations and impacts (I. Tussyadiah, 2020), with a strong interest in service robots. However, no study has adopted empirical methods to forecast how AI, and specifically, which AI technologies will impact the industry in the near future. By focussing on VC-backed AI technological domains, this study attempts to understand the AI technologies that will be developed further because of the higher availability of financial resources. Furthermore, a closer look at the technologies being developed for the different stages of the travel journey (i.e. pre-trip, during the trip, post-trip) will provide insights on the stages of the travel planning that will be impacted the most by AI solutions (I. Tussyadiah, 2020).

This study attempts to fill these gaps in the travel and tourism literature, and by doing so, we respond to a call for contributions to digital entrepreneurship (Fu et al., 2019; Nambisan et al., 2019; Obschonka & Audretsch, 2020; Zaheer et al., 2019) and AI research in tourism (I. Tussyadiah, 2020). Hence, this study attempts to answer the following three research questions:

RQ3. What are the characteristics of VC-backed tourism AI start-ups?

RQ4. What are the VC-backed AI start-ups technological domains??

RQ5. What is/are the phase/s of the tourism supply chain where AI start-ups received the highest amount of funding from VCs?

To answer these research questions, we adopted a mixed-method approach. Firstly, we developed a proprietary database of tourism AI start-ups drawing upon the whole population of the European's VC-backed AI start-ups from the CrunchBase database. Secondly, we gathered additional information from the LinkedIn profile of the start-up founders and the company's website using the NVivo software to analyse them. The contents of this chapter have been taken from a published paper to the Special Issue of the International Journal of Contemporary Hospitality Management "Artificial intelligence (AI) for tourism" with the title "Artificial intelligence (AI) for tourism: an European-based study on successful AI tourism start-ups" (Filieri et al., 2021).

4.2 Literature review

McCarthy (2007) points out that AI allows machines to perform complex and intelligent tasks or, more precisely, to achieve many of the activities that are traditionally associated with reasoning and human intelligence (Russell & Norvig, 2020). The European Union (EU) Independent High-Level Expert Group on Artificial Intelligence (2020) refers to AI systems as follows: *"[.. .] software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal."*

In academic terms, scholars investigate “how digital computers and algorithms perform tasks and solve complex problems that would normally require (or exceed) human intelligence, reasoning, and prediction power needed to adapt to changing circumstances” (Obschonka & Audretsch, 2020, p 530)

Currently, academic debate on AI is mainly at the conceptual level, focussing on the benefits and risks deriving from the implementation of physical robots in the hospitality sector (Belanche, Casaló, & Flavián, 2020; Ivanov & Webster, 2019a; Murphy et al., 2017; Samara et al., 2020; Tung & Law, 2017; I. Tussyadiah, 2020). For instance, Ivanov and Webster (2019a) proposed a conceptual framework to explain the adoption of robotics, AI, and service automation in the tourism industry, underlining the prominent role of the final customers’ attitude towards accepting these new technologies. Murphy et al. (2017), Tung and Law (2017) and Tussyadiah (2020) review and systematise the travel and tourism literature and discuss the benefits and risks of intelligent automation, proposing a research agenda. Other studies analysed the determinants of consumers’ perceptions and acceptance of service robots Belanche et al. (2020a), Yu (2020) or proposed the concept of smart tourism to describe a tourism ecosystem permeated by technologies, amongst which AI can create new value because of data and interconnections (Buhalis & Sinarta, 2019; Gretzel et al., 2015).

AI is also believed to cause fundamental shifts in many sectors (Flavián, Pérez-Rueda, Belanche, & Casaló, 2021), with start-ups playing a pivotal role (Groen et al., 2008; Nanda & Rhodes-Kropf, 2013). However, despite the growth of AI start-ups, there is a shortage of studies on the entrepreneurial activities of these companies (Chalmers et al., 2020; Obschonka & Audretsch, 2020). Furthermore, there is a scarcity of research on the intersection between tourism and entrepreneurship Solvoll et al. (2015) and even more on digital entrepreneurship in the tourism context (Fu et al., 2019; Nambisan et al., 2019; Zaheer et al., 2019). Existing studies on tourism entrepreneurship have focussed on the motivations of tourism entrepreneurs for starting a new venture Bosworth and Farrell (2011) and on typologies of tourism entrepreneurs (i.e. growth-oriented or lifestyle-oriented entrepreneurs) (Bredvold & Skålén, 2016; Getz & Peterson, 2005). Other studies have reviewed the tourism entrepreneurship literature (Fu et al., 2019; Solvoll et al., 2015; Thirumalesh Madanaguli, Kaur, Bresciani, & Dhir, 2021) or they have investigated the antecedents of entrepreneurship performance, such as the effects of educational level, online promotions, new product development (Hernández-Maestro & González-Benito, 2014), place identity, self-efficacy (Hallak, Brown, & Lindsay, 2012), gender (Hallak et al., 2015) and proactiveness, innovativeness, risk-taking, networking and financial resources (Kallmuenzer, Kraus, Peters, Steiner, & Cheng, 2019).

Most empirical research in tourism is based on small and often family-managed hospitality businesses, and fewer studies have focussed on digital entrepreneurship in tourism. Digital entrepreneurship is increasingly relevant in the TTI, where major digital companies, such as Airbnb, Tripadvisor, Booking and Skyscanner have fostered a radical change in the sector. These players are redefining the tourism industry ecosystem and the way tourism actors operate and market their services. However, these companies may struggle to embrace new technological products and services, which are often introduced by start-ups (Markides, 2006). AI start-ups, such as DeepL, Fetch.ai and Lilium, are expected to be the first to introduce innovative AI solutions in the travel sector. Start-ups think and move faster than established companies, and they are best at exploiting the opportunities offered by disruptive innovations before others. Investors have a crucial role in selecting and funding the most promising technological solutions.

To advance the digital entrepreneurship literature, our study aims to investigate the internal factors of successful AI start-ups or the founder's human capital (Ko & McKelvie, 2018), which play an important role in the process of start-ups' creation (Obschonka & Audretsch, 2020; Welter, Baker, & Wirsching, 2019). This study also investigates the technological domains that are receiving the highest amount of funding from VC; hence shedding light on the AI technological solutions considered more promising, and that will affect the tourism market and its actors. VCs will fund only activities that they value as highly rewarding, hence, highly impactful on the market. Finally, we shed light on the phases of the tourism supply chain that will be more affected by the AI solutions developed by AI start-ups, trying to reveal the stages of the traveler journey that will be most impacted by AI technologies.

4.3 Methodology

4.3.1 Data collection and sampling

We focussed on the European AI context because it is amongst the major players in the AI industry (Tractica, 2019). We used the Crunchbase database, the largest database of funded start-ups with over 1,000,000 company profiles from more than 200 countries, which reports information about the technological domain of every start-up, investors and founders (Kim, Kim, & Sohn, 2020). Our observation period was of 16 years, between January 2005 and December 2020. The resulting data set included 4,469 AI start-ups; from this data set, we selected the AI start-ups operating in the tourism industry (Figure 7). The identification of tourism AI start-ups was performed by a Python web-scraper that browsed the website of the AI start- ups searching for keywords identified by means of content analysis (through Nvivo) of four academic books on tourism (McAdam, Bateman, & Harris, 2005; Medlik, 2003; Sharpley, 2006; Swarbrooke & Horner, 2001). The keywords chosen from the most representative concepts were, namely, tourism, hotel, destination, tour, holiday, accommodation, visitors, airline, leisure, attraction, guest, flight, passenger, travel, room, tourist, vacation, airway, attractiveness, travel agency, hospitality. We then checked whether the websites of the AI start-ups contained at least two of these keywords and discarded those that did not contain them (N = 3,161 start-ups). The website of 807 start-ups was not accessible due to technical malfunctioning (i.e. page not existing/not reachable); therefore, these start-ups were excluded from the final sample.

During the classification steps, better described in the next section, we applied additional filters to the remaining start-ups to exclude those who did not have a clear and explicit reference to AI technology on their website. The selection process returned a list of 92 AI tourism start-ups.

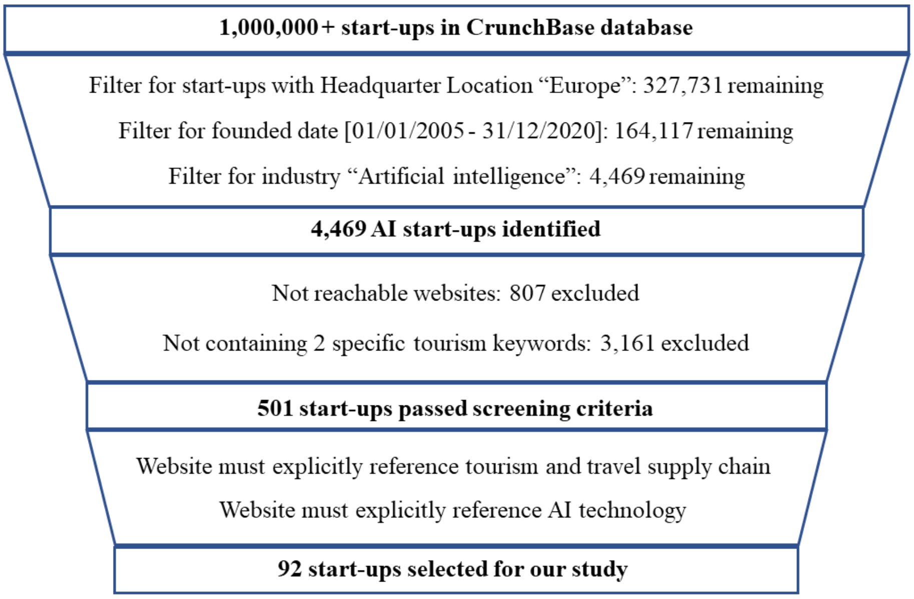

Figure 7: Tourism start-ups selection process

4.3.2 Data classification and variables operationalisation

We classified start-ups according to the following two axes:

(1) The phases of the supply chain they are targeting; and

(2) The AI technological domains they are operating in.

The classification procedure is explained in detail in Appendix 3.

Table 12 provides information about the operationalisation of the start-up in terms of geographical location, year of foundation, funding received and features of the team. Such characteristics are relevant for predicting the success of a new venture (Hallak et al., 2015), indicating, for example, that demographic aspects make a difference in the outcome of entrepreneurial activities (Fu et al., 2019). The Crunchbase database contains information about start-ups, such as headquarter location, foundation date and founders' names. Following the approach adopted in other studies (Debreceny, Wang, & Zhou, 2019), we gathered additional information about the founders (i.e. gender and work experience) from their LinkedIn profile (Table 12).

Table 12: Operationalization of variables, characteristics of the entrepreneurial team

Variable	Operationalization	Sources	Reference
Headquarters location	Location of start-up headquarters	Crunchbase.com	Chatterji *et al.*, 2017; Dahl and Sorenson, 2012
Date of foundation	Date of start-up foundation	Crunchbase.com	Chatterji *et al.*, 2017
Total Funding Amount	Amount of funding collected by the start-up, in US dollars	Crunchbase.com	Camuffo *et al.*, 2019
Number of founders	Number of founders	Crunchbase.com	Lechler, 2001
Team percentage female	Percentage of female founders	LinkedIn	Hoogendoorn *et al.*, 2013
Team percentage STEM	Percentage of founders holding STEM degree	LinkedIn	Jo and Lee, 1996
Team percentage PhD	Percentage of founders having a PhD	LinkedIn	
Team percentage MBA	Percentage of founders having an MBA	LinkedIn	Camuffo *et al.*, 2019
Team percentage company experience	Percentage of founders having working experience in companies	LinkedIn	Chatterji *et al.*, 2017
Team percentage start-up experience	Percentage of founders having working experience	LinkedIn	Chatterji *et al.*, 2017

A technological domain defines the scope and the working principle of an AI-based solution. This study adopted the classification of AI technological domains developed by the European Commission (EU)'s Joint Research Centre (Samoili et al., 2020). The EU classification includes the following macro-domains: *Reasoning, Planning, Learning, Communication, Perception, Integration and Interaction, Services, Ethics and Philosophy* (Table 13) (Samoili et al., 2020). We considered the keywords included in the EU classification to assign each start-up to an AI technological domain following the same approach used in the previous phase (Appendix 4). We verified the presence of keywords of the specific AI technological domain on the AI start-up websites. For example, we assigned start-ups developing chatbots to the *Communication* domain, start-ups dealing with virtual reality to the *Perception* domain, and start-ups offering service robots or optimal allocation of scarce resources to the *Planning* domain. Table 13 contains a brief description and some examples of the AI technological domains and sub-domains.

We operationalised the phases of the supply chain of each start-up with five dummy variables, representing five phases, as illustrated in Figure 8. Figure 9 instead provides some examples of the start-ups that have received the highest amount of funding. Each phase is detailed in Table 14, including some examples. As start-ups may decide to operate simultaneously at different supply chain stages, we also considered that start-ups could offer services in more than one phase.

Table 13: Operationalization of variables, AI technological domains and sub-domains.

AI technological domains	Description	AI subdomain	Reference
Reasoning	It represents how machines transform input (i.e., data) into information and knowledge. It makes use of symbolic rules to represent and infer knowledge.	Knowledge representation Automated reasoning Common sense reasoning	McCarthy, 2007
Planning	It is the domain of the representation and implementation of strategies formed by sequential activities performed by unsupervised machines and/or autonomous robots; the solutions belonging to this domain are complex and optimized in a multidimensional space.	Planning and scheduling Searching Optimization	McCarthy, 2007
Learning	It is the ability of systems to automatically learn, decide, predict, adapt and react to changes, improving from experience without being explicitly programmed.	Machine Learning	McCarthy, 2007

Communication	It is the domain that refers to the abilities to identify, process, understand, and generate information and documents in written and spoken language by humans. Its applications are related to text generation, classification, and translation.	Natural language processing (i.e., Chatbots)	McCarthy, 2007; Talwar and Koury, 2017
Perception	It represents the ability of the system to become aware of the surrounding environment through the use of senses (vision, hearing, touch, smell). This domain includes computer vision, which refers to activities that identify human faces and objects, and audio processing, which is dedicated to the perception and generation of audio signals, such as speech or sounds in general.	Virtual reality Face recognition Audio processing	McCarthy, 2007; Talwar and Koury, 2017
Integration and Interaction	It combines all the features described above (from reasoning to perception) and their interaction with the surrounding environment in order to introduce features of cooperation, integration, and interaction.	Multi-agent systems Robotics and automation Connected and Automated Vehicles	McCarthy, 2007
Services	It refers to facilities, platforms, and software capable of providing services and applications executed on demand and always available, reducing the management of the physical infrastructure of enterprises (cloud storage and computational power). These services include the following: Infrastructure as a Service, Platform as a Service, and Software as a Service.	AI Services	Talwar and Koury, 2017
Ethics and Philosophy	This domain brings together activities to ensure compliance with ethical principles and values, including applicable regulation.	AI ethics and philosophy	McCarthy, 2007

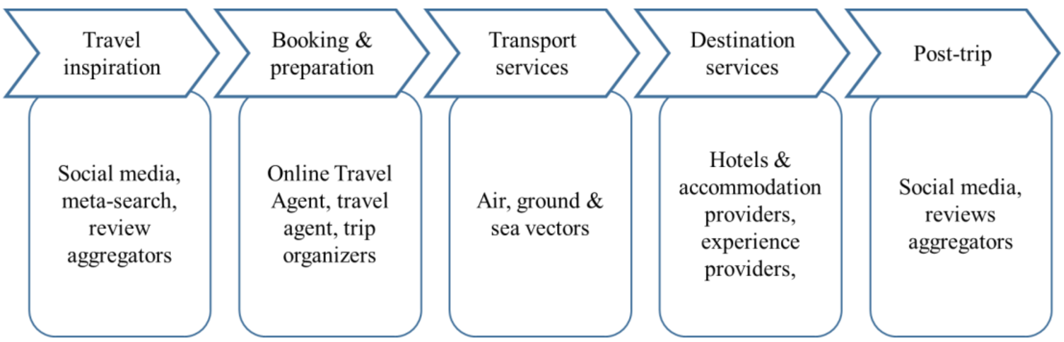

Figure 8: Key players in the tourism supply chain

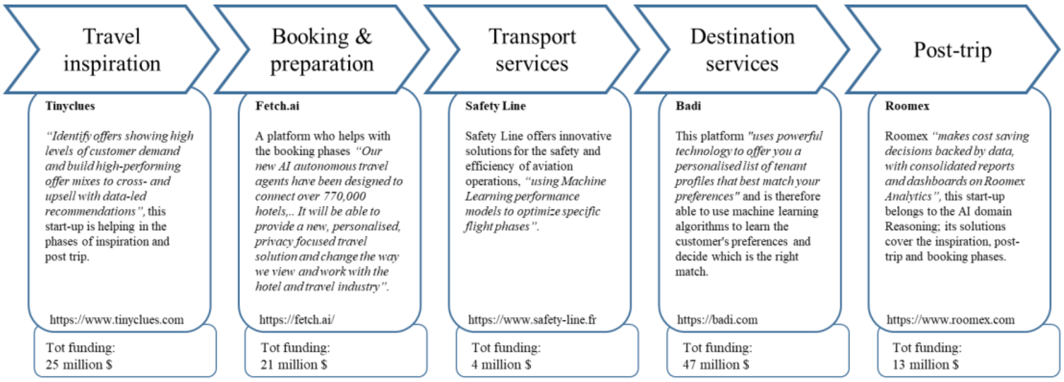

Figure 9: Start-up examples

4.4 Findings

4.4.1 Characteristics of tourism artificial intelligence start-ups

The first research question posited: *"What are the internal characteristics of VC-backed AI tourism start-ups?"* Table 15 provides the descriptive statistics about the tourism AI start-ups detailing the founders' education (i.e. education degree), working experience and gender. Interestingly, findings show that start-up founders are "distant" from university research environments due to the scarcity of PhDs (13%) and MBAs (6%) amongst founders. Furthermore, 30% of founders have a Science, Technology, Engineering and Mathematics (STEM) background. In total, 18% of start-up founders do not have a previous experience as start-uppers. Still, they have previous working experience in the tourism industry and 93% of them are male.

Table 14: Operationalization of variables, Supply chain phases

Trip phase	Supply chain phase	Description	Reference
Pre-trip	*Travel inspiration*	Start-ups involved in creating awareness about tourism services and destinations. Start-ups in this phase focus on benchmarking with other tourism services and destinations, managing online visibility, and customer acquisition.	World Economic Forum, 2017
Pre-trip	*Booking and travel planning*	Start-ups offering solutions linked to the processes of booking and planning. This category includes chatbot solutions to book tourism services, dynamic pricing solutions, software able to suggest and book itineraries and activities.	Fong et al., 2021; Romero and Tejada, 2011; World Economic Forum, 2017
Trip	*Transportation services*	Start-ups in this phase are linked to transportation and target airline consumers, suggesting the best routes for the vectors, making the check-in process faster and more secure.	Fong et al., 2021; Romero and Tejada, 2011; World Economic Forum, 2017

Trip	*Destination services*	Start-ups focusing on tourist experience at the destination. Examples of the services are the check-in services at the destination, recommender systems, people tracking, and analytics.	Fong et al., 2021; Romero and Tejada, 2011; World Economic Forum, 2017
Post-trip	*Post-trip*	Start-ups perform data analysis of customers' feedback (i.e., reviews) and monitor brand reputation.	World Economic Forum, 2017

Considering the correlations in Appendix 2, it is interesting to note that the start-ups that received the highest amounts of funding from VCs are more likely to have a higher number of founders with previous working experience. Interestingly, there is no significant correlation between the total amount of funding received by start-ups and internal variables, such as the founders' educational level, previous start-up experience, gender and the number of investors.

Table 15: Descriptive statistics

	Total Funding (thousand $)	Number of Founders	Number of Investors	% Female	% STEM Graduate*	% PhDs	% MBAs	% Company Experience	% Start-up Experience
Min	9	1	1	0%	0%	0%	0%	0%	0%
Max	46,863	6	11	100%	100%	100%	100%	100%	100%
Average/ Percentage	5,988	1.99	3.29	7%	30%	13%	6.0%	61%	18%
Standard deviation	9,045	1.06	2.43	21%	41%	30.0%	19%	45%	35%

*Notes: *STEM stands for Science, Technology, Engineering, and Maths graduates.*

With an average of almost 6 million funding (the maximum funding is close to € 50m), tourism AI start-ups appear to be well funded by investors since, on average, young start- ups' pre-money valuation can be estimated at around € 6m (Miloud, Aspelund, & Cabrol, 2012). Considering the distribution of the year of the start-ups' foundation (Figure 10), we can observe a declining trend since 2017. More than 50% of AI tourism start-ups were established between 2015 and 2017. This declining trend could be due to the AI technology's perceived "maturity" and limited market segments to serve.

Table 16: AI tourism start-ups' headquarters

Start-up headquarters location	Number	Frequency	Cumulated Frequency
London, United Kingdom	24	26.09%	26.09%
Paris, France	8	8.71%	34.80%
Barcelona, Spain	4	4.36%	39.16%
Tallinn, Estonia	2	2.17%	41.33%
Madrid, Spain	2	2.17%	43.50%
Lisbon, Portugal	2	2.17%	45.67%

Lausanne, Switzerland	2	2.17%	47.84%
Moscow, Russian Federation	2	2.17%	50.01%
Berlin, Germany	2	2.17%	52.18%
Helsinki, Finland	2	2.17%	54.35%
Munich, Germany	2	2.17%	56.52%
Others	42	43.48%	100.00%

Tourism AI start-ups show a high concentration in few geographical areas. To understand the role of geography, we mapped the location/city where start-ups have been founded (Table 16 reports the first 11 cities). Almost 40% of the AI tourism start-ups were born in three European capitals; London alone accounts for 26% of all AI start-ups (24) whilst Paris accounts for 8.7% (8) and Barcelona for 4.4% (4). This result highlights that start-ups providing AI solutions are mainly located in the capital town of the most famous European tourism destinations, the UK with London, France with Paris and Spain with Barcelona. In these countries, tourism is a significant voice in the GPD.

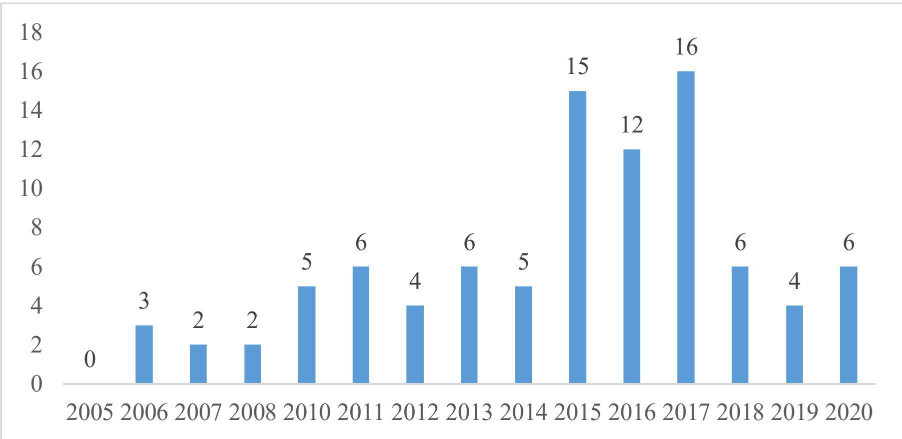

Figure 10: Number of AI tourism start-ups per year of foundation

4.4.2 Artificial intelligence start-ups and technological domain

The second research question of this study asked: *"What are the VC-backed AI technological domains?"*. To respond to this research question, we followed various steps. Firstly, we run a correlation analysis (Appendix 2) to assess the relationship between the total funding (TF) received by start-ups and the AI technological domain. Data analysis reveals a positive correlation with the Learning domain, highlighting a growing interest in machine learning and big data solutions. On the contrary, Perception is the only AI technological domain with a negative correlation with Total Funding. Furthermore, through NVivo, we analysed the most frequently appearing keywords on the website of AI start-ups backed up by VC and for each stage of the tourism supply chain (Table 17). Interestingly, security, safety and transparency are the most frequent keywords across all the phases, meaning that many start-ups feel the need to stress the safety and security of their data storage and solutions (without being cyber-security companies). Further, big data is amongst the most frequent keywords almost in all the phases, highlighting that big data and AI are often intertwined and go hand in hand as drivers of the current digital transformation in society (Brynjolfsson & McAfee, 2014). Finally, the chatbot is another keyword often mentioned on AI start-up websites, particularly for booking and preparation and destination services. Overall, these results indicate the growing attention paid to AI-related security and privacy issues, as well as automation of customer service and big data analytics.

Table 17: Frequency of keywords per tourism phase

Travel inspiration		**Booking and preparation**		**Transportation services**		**Destination services**		**Post-trip**	
Keyword	N	Keyword	N	Keyword	N	Keyword	N	Keyword	N
Security	**15**	**Security**	**15**	**Security**	**11**	**Security**	**13**	**Security**	**6**
Safety	**7**	**Chatbot**	**13**	**Safety**	**6**	**Big data**	**7**	**Safety**	**5**
Big data	**6**	**Safety**	**6**	**Big data**	**4**	**Safety**	**6**	**Transparency**	**4**
Transparency	**5**	**Big data**	**4**	Face recognition	3	**Virtual reality**	**5**	Sentiment analysis	2
Virtual reality	3	**Transparency**	**4**	Recognition technology	3	**Chatbot**	**4**	Chatbot	2
Clustering	2	Neural network	2	Deep learning	2	Business intelligence	3	Boosting	1
Deep learning	2	Business intelligence	2	Neural network	2	Data analytics	3	Deep learning	1
Chatbot	2	Data analytics	2	Chatbot	2	Deep learning	2	Game theory	1
Machine translation	2	Personal assistant	2	Classification	1	Neural network	2	Big data	1
Analytics platform	2	Expert system	1	Data mining	1	FAce recognition	2	Data analytics	1
Business intelligence	2	Boosting	1	Pattern recognition	1	Recognition technology	2	Fairness	1
Data analytics	2	Data mining	1	Image processing	1	Boosting	1		
Boosting	1	Deep learning	1	Autonomous vehicle	1	Classification	1		
Classification	1	Recommender system	1	Business intelligence	1	Pattern recognition	1		
Neural network	1	Support vector machine	1	Fairness	1	Reinforcement learning	1		
Pattern recognition	1	Computational linguistics	1	Transparency	1	Sentiment analysis	1		
Sentiment analysis	1	Natural language understanding	1			Visual search	1		
Text mining	1	Sentiment analysis	1			AI application	1		
AI application	1	Image processing	1			Analytics platform	1		
Internet of things	1	AI application	1			Decision support	1		
		Internet of things	1			Internet of things	1		
		Machine-learning framework	1			Personal assistant	1		
		Machine-learning platform	1			Virtual environment	1		
		Artificial general intelligence	1			Transparency	1		

Secondly, Table 18 presents a heat-map (i.e. a representation of data in a diagram where data values are represented as colours and the darker colour highlights higher values), with the TF received. This map shows the relations between the average funding received (in parenthesis) by each start-up, the supply chain phases and AI domains of application. We used the number of start-ups funded by the supply chain phase and AI technological domains to compute these data, as shown in Appendix 5.

Specifically, the data in the columns in Table 18 show that the start-ups that received the majority of funding provide AI applications in the Services domain followed by the AI domains of Learning and Communication. The AI Services technological domain refers to any infrastructure, software and platform (e.g. cognitive computing; machine learning frameworks, library and platforms; chatbots and virtual assistants; internet of things) provided as (serverless) services or applications, possibly in the cloud, which are available off the shelf and executed on-demand, reducing the management of complex infrastructures (Samoili et al., 2020). The AI domain of Learning refers to the ability of AI systems to automatically learn, decide, predict, adapt and react to changes, improving from experience, without being explicitly programmed (Samoili et al., 2020). The AI domain of Communication refers to the ability to identify, process, understand and/or generate information in written and spoken human communications (Samoili et al., 2020).

These three technological domains relate to the automation of customer service and relationship management and marketing intelligence, allowing companies to operate more efficiently on a larger scale and generate insights from a larger amount of data. These AI technologies are aimed at improving the effectiveness of marketing communications, customer segmentation and behaviour forecast. Specifically, AI can provide large customer data that is needed to segment customers from a global market perspective. AI start-ups can leverage these data for providing cross-selling services opportunities with direct outcomes on revenue generation. Appendix 6 also shows the co-occurrences of the start-up's domains of application (single versus multiple domains), highlighting that most start-ups operate only in one AI technological domain. Moreover, most start-ups (76%) focus on a single stage of the tourism supply chain whilst the remaining 24% focus on two or more phases (Appendix 7). This result highlights that start-ups that develop AI solutions for the tourism industry are more likely to specialise in a single stage of the supply chain rather than providing solutions for various phases, leveraging specific competencies and knowledge related to a particular aspect of the service.

Table 18: The total amount of funding received by start-ups (in thousands of $)

	AI technological domains								
Supply chain phases	*Reasoning*	*Planning*	*Learning*	*Communication*	*Perception*	*Integration and Interaction*	*Services*	*AI Ethics and Philosophy*	**Total**
Travel inspiration	13,030 (13,030)	-	88,827 (22,207)	47,390 (7,898)	76 (76)	-	103,043 (11,449)	-	**252,366**
Booking and Preparation	13,030 (13,030)	-	46,863 (46,863)	18,363 (3,060)	-	-	96,292 (10,699)	21,000 (21,000)	195,548
Transport services	-	-	7,864 (1,573)	-	6,070 (3,035)	11,294 (11,294)	5,884 (1,471)	3,520 (3,520)	34,632
Destination services	-	-	46,975 (23,487)	8,223 (4,112)	347 (116)	-	65,134 (10,856)	14,033 (7,017)	134,712
Post-trip	13,030 (13,030)	-	72,234 (36,117)	44,560 (8,912)	-	-	59,233 (29,617)	-	189,058
Total	39,090	-	262,763	118,536	6,494	11,294	329,586	38,553	806,318

Note: every cell contains the total funding crossing the supply chain phases and AI technological domains of application, and in parenthesis, it is specified the average funding for every start-up.

4.4.3 Artificial intelligence technological domains and tourism supply chain phases

The third research question posited the following:: *"What are the phase/s of the tourism supply chain where AI technological domains received the highest amount of funding from VCs?"*. To respond to this research question, we run a correlation analysis (see rows in Appendix 2) between the phases of the tourism supply chain and the total amount of VC funding. These results of the correlation analysis show that Travel inspiration, Booking and preparation and Post-trip have a positive correlation with TF, suggesting that these stages are receiving more funding. This is also confirmed by data contained in Table 18. This result implies that AI technologies will have a major impact on specific phases of consumers' travel planning in the future. Overall, the tourism supply phases that received more funding refer to the pre-trip and post-trip phases, highlighting the interest in AI solutions aimed at understanding customers' needs before the trip and their experiences after a trip.

4.5 Conclusions

We explored the internal characteristics of AI start-ups operating in the tourism industry because internal factors, such as demographic variables, are relevant for predicting the success of a new venture (Hallak et al., 2015), which advance the digital entrepreneurship literature (Elia et al., 2020; Kraus et al., 2019). By focussing on AI start-ups that have been successful in securing VC funding, our results show that AI ventures are mainly created by male STEM graduates with previous company experience. These findings support the gender gap in entrepreneurship orientation and the women-STEM-avoidance found in the socio-psychological Ruef et al. (2004), Thébaud and Charles (2018) and the entrepreneurship literature (Guzman & Kacperczyk, 2019). Guzman and Kacperczyk (2019) show that start-ups led by women are less likely to access VC funding, and the portion of the gap is higher with regard to gender differences in initial start-up orientation. The gendered theory suggests that women will be affected by their career choice, which will drive them towards start-ups associated with lower growth potential (Ruef et al., 2004). Furthermore, investors perceive women as less competent entrepreneurs because of their childcare obligations (Guzman & Kacperczyk, 2019; Thébaud, 2015). We also reveal that most of the founders of tourism AI start-ups do not have a high level of education, but they have previous work experience in non-start-up companies. Hence, our study also links to the literature on the effect of the founders' human capital in acquiring first-round financing from VCs (Ko & McKelvie, 2018). Contrarily to Ko and McKelvie (2018), our study shows that the founders' previous work experience is positively correlated with the total amount of funding received whilst the level of education was not. This result enables us to contribute to the human capital theory, which assumes that an individual's performance outcome is related to their skill and knowledge levels (B. C. Martin, McNally, & Kay, 2013), and increased performance and productivity levels can be expected with increased human capital (Schultz, 1961). Our results show that the entrepreneur's degree of education is not correlated with the capacity to secure higher levels of funding. This result contrasts with studies on rural tourism entrepreneurship, where the entrepreneur's level of education was significantly related to enterprise performance (Hernández-Maestro & González-Benito, 2014). This finding is also not consistent with the entrepreneurship literature suggesting that education has positive effects on entrepreneurial performance (Oakey, 2012; Van Der Sluis, Van Praag, & Vijverberg, 2008) and on the entrepreneur's exploitation of business opportunities (Davidsson & Honig, 2003). Moreover, our findings do not confirm that technical education at a doctorate level or higher levels of education, increases the probability of exiting a start-up or increases the chances of receiving funding significantly (Ratzinger, Amess, Greenman, & Mosey, 2018).

Interestingly, we noticed a declining trend in the rate of creation of AI start-ups, with a peak in 2015–2017 where almost half of all European start-ups operating in the tourism sector have been created. According to the literature, this relevant level of investment in AI start-ups is due to expectations of high growth and industry disruption (von Briel, Davidsson, et al., 2018). The peak is consistent with the mechanisms of VC funding and start-up creation: usually, they happen in cycles; when more experienced actors take a direction, they generate a crowd of followers that leads to a peak (Nanda & Rhodes-Kropf, 2013). Afterwards, the number of ventures diminishes whilst the market observes the performance of the first wave of start-up creation and investments (Nanda & Rhodes-Kropf, 2013).

Our findings show a concentration of tourism AI start-ups in some geographical areas, specifically in the major European tourism destinations (France, UK and Spain). This finding links to previous studies on the role of geography in tourism entrepreneurship (Debbage & Ioannides, 1998; Massey, 1995) and configures the dynamics of the regional advantage observed by Saxenian (1996) in the Silicon Valley, based on the advantages achieved because of a supportive regional environment. The "regional advantage" configures a geographical concentration phenomenon of knowledge and capabilities where there are already resources, technical/digital capabilities and path-dependence phenomena (R. Martin & Sunley, 2006; Saxenian, 1996). Hence, we may expect that tourism companies and organisations operating in these countries will probably benefit from AI solutions the most and lead the change in the tourism industry.

Furthermore, we examined the AI technological domains that have received more funding from VCs, and we linked them to the stages of the tourism supply chain. The results show that Learning, Communication, and Services, are the AI technological domains where European start-ups received the most funding. This result indicates a strong interest in systems that are able to interact with consumers, understand their needs and requests, and provide customised answers/services. AI technological domains that will potentially grow more relate to big data, machine learning, chatbots and digital platforms. AI solutions that will be de prominent in the travel industry are those that develop digital algorithms Belanche et al. (2020b) to gather and analyse big data about customers' behaviour, and are able to identify patterns and generate insights from these data. Travel companies will be using AI solutions, particularly for marketing purposes and specifically to learn from existing data and apply this knowledge to new data or use it to predict phenomena. For instance, the data can be used to automatically develop customised communications and solutions that satisfy the needs of micro customer segments. For instance, some business-to- business companies (i.e. Fetch.ai) offer AI-based booking systems to travel agencies, which can offer personalised accommodation services to their customers. Tinyclues, another AI tourism start-up, enables to find early and late bookers and strategically time offers, and to identify high-performing offers (i.e. emerging destinations) and build customised travel offers. AI technologies will increasingly allow marketing managers to operate more efficiently and on a larger scale, which will improve their ability to create insights and forecast consumer behaviour through the analysis of big data. Interestingly, we showed that Planning, Perception, Integration and Interaction are the AI technological domains that received very limited amounts of funding, implying that the European tourism industry is less interested in AI applications, such as virtual reality, robotics, and automation, connected and automated objects and resource allocation. Hence, although consumer perception of service robots and their reactions to their hypothetical and actual use has received significant interest in academia, particularly in service industries research, its implementation in the European tourism industry will be minimal.

Interestingly, we revealed that “security”, “safety” and “transparency” are keywords that frequently occur on AI tourism start-up websites and across all the stages of the tourism supply chain. This result indicates that European tourism operators/consumers want to be reassured about the safety and security of AI solutions, highlighting the importance of privacy issues in AI (Samala, Katkam, Bellamkonda, & Rodriguez, 2020; Wang & Siau, 2018). This finding supports the results of previous studies on disruptive technology policies suggesting that the EU takes a precautionary approach with much more prohibitive policies intended to protect data privacy compared to other countries (i.e. USA) (Pesapane, Volonté, Codari, & Sardanelli, 2018). Precautionary principle reasoning refers to the belief that innovations should be curtailed or disallowed until their developers can demonstrate that they will not cause any harm to individuals, groups, specific entities, cultural norms or various existing laws or traditions.

We revealed that most of the start-ups focus on a single stage of the supply chain, highlighting that most of them leverage capabilities and knowledge related to a specific area of travel planning. Most AI start-ups provide solutions for Travel Inspiration, Booking and Preparation and the Post-Trip stage, demonstrating the need for data analysis on travellers' online behaviours mainly related to the Pre-trip and Post-trip phases. Travel inspiration will benefit from intelligent automation in the pre-trip stage of traveller's activities (i.e. travel information and experiences search and reservations) (I. Tussyadiah, 2020). AI applications will be eventually used for omnichannel marketing automation to scale marketing content globally, offer customised offers, ease the online shopping experience and attract and manage leads (I. Tussyadiah, 2020). Big data, analytics and chatbots are the AI solutions that recorded the highest investors' interests for these stages.

4.5.1 Theoretical contribution

This study responds to a call for contributions to digital entrepreneurship (Elia et al., 2020; Fu et al., 2019; Kraus et al., 2019; Nambisan et al., 2019; Zaheer et al., 2019), and specifically to the emerging entrepreneurship-AI intersection (Obschonka & Audretsch, 2020). Start-ups and digital technologies are continuously disrupting the business environment and modifying consumer behaviours. However, there is little research on digital entrepreneurship and even less on the intersection between AI/Big Data and entrepreneurship (Chalmers et al., 2020; Obschonka & Audretsch, 2020). This study also contributes to the growing research on entrepreneurship (Debbage & Ioannides, 1998; Fu et al., 2019; Solvoll et al., 2015) and AI in tourism (I. Tussyadiah, 2020), making a methodological contribution by adopting a combination of research techniques in the study of tourism entrepreneurship, which was limited to surveys and case studies (Solvoll et al., 2015). Although scholars suggest that any predictions and explications of future scenarios might quickly become outdated due to the rapid progress in the fields of AI and big data (Obschonka & Audretsch, 2020), overall, our findings contribute to advancing knowledge about AI start-ups, and in predicting what AI technologies will influence, which phases of the tourism supply chain the most in the near future.

4.5.2 Practical implications

Through this study, companies can learn the AI trends in the tourism industry, specifically the AI solutions that will receive relevant resources for their implementation and commercialisation. Our study can also help entrepreneurs of large digital companies to identify threats and opportunities to their business with regard second-order to the AI technological domains of application that will be commercialised in the recent future so that they can eventually consider integrating them into their operations at an early stage.

We revealed a strong interest in companies providing solutions in the pre-trip and post-trip stages of tourism planning, confirming there is a high interest in technologies, such as big data, data analytics, machine learning and chatbot. We showed that VC-backed AI technological solutions are those used for marketing automation, customer service and relationship management (i.e. chatbot for customer queries and complaint handling), which can potentially impact the effectiveness of marketing and sales' activities.

Most start-ups are created by male entrepreneurs with previous work experience in the European capitals of advanced economies and with large tourism flows (London, Paris and Barcelona). This result means that these cities are developing absorptive capacity and specialisation in the technological domain of AI, which will create a solid base for future growth and the potential development of research excellence centres, AI-based clusters like in the Silicon Valley or the Cambridge Cleantech. The specialisation of some countries may also attract more funders and companies in the future, leading to the creation of new jobs.

4.5.3 Limitations and future research

The limitations of the current study are various. Firstly, even though we identified the supply chain phases and AI solutions on which VCs are investing, we cannot forecast how value appropriation dynamics will develop in the long-term. Secondly, the focus of this study was the European entrepreneurial ecosystem; even though it is reasonable to generalise our finding at the worldwide level, it might be worth comparing it with the American and Asian ecosystems where AI start-ups may receive higher funding to develop other solutions, such as robotics or facial recognition. Thirdly, future research could investigate other entrepreneurial factors, such as personality traits, demographic characteristics (i.e. age) and digital capabilities in explaining their creation and growth potentialities. Fourthly, interviews with funders could be conducted in future research to provide a more in-depth understanding of the industry, the entrepreneur and the future of AI applications in the tourism industry. Future research could focus on understanding what the tourism operators should do to capture the value created by AI solutions for improving their operational activities. Finally, privacy and security appear to be core issues in the AI industry. Future research could investigate what business and final consumers think of these issues to implement solutions that can minimise their concerns.

Chapter 5

Thesis conclusions

5.1 Introduction

This thesis aims at better understanding and disentangling some of the aspects characterizing the process of change that tourism industry is undergoing due to the development of innovative business models based on general purpose technologies advancement.

In the first part of the thesis, whose conclusions are going to be discussed in chapter 5.2, two different sets of quantitative analysis have been performed in order to quantify the impact of digital accommodation platforms diffusion in two different contexts: the context of large size, famous and established touristic destinations and the context of small, rural and less-known areas. For the big, established destinations, literature shows a growing intolerance from many components of the community, being them incumbents losing economic figures or citizen excluded to access some resources to favour the tourists. For the less-known areas willing to increase their touristic attractiveness potential on the other hand, literature seems to indicate the digital accommodation platforms as a mean to mitigate or eve reverse some negative phenomena such as depopulation and impoverishment.

In the second part of the thesis, whose conclusions are going to be discussed in chapter 5.3, a quali-quantitative analysis has been performed in order to estimate future changes in tourism industry structure. The analysis examines the characteristics of artificial intelligence start-ups targeting tourism industry in terms of antecedents, AI domain of application utilized and phase of tourism supply chain targeted. Examining the size of the investment received by each category of start-ups it has been possible to estimate which phases of tourism supply chain will more likely be subject to changes in the near future and which kind of application of artificial intelligence will make this change possible.

From a high level perspective, this thesis contributes to the literature that analyses the impact of general purpose technology enabled business models on tourism industry (Guttentag, 2015; Nambisan, 2016; Zaheer et al., 2019).

5.2 Current consequences of digital platforms diffusion

In the introduction of Thesis conclusions chapter, the double side effect of digital accommodation platforms in accommodation and hospitality market has been underlined. One of the way we explain this discrepancy is noting that scarce resources demand form the communities is much higher in big cities than in small villages. Space, for example, is a scarce resource in most big cities, both the creation of accommodation for the tourists and the tourists take space once available for residents, with a series of negative consequences such as more traffic, more time spent queuing for basic services, more difficulty in finding space for living(González-Pérez, 2020; Sequera & Nofre, 2018; Wachsmuth & Weisler, 2018). This competition also pushes prices to rise relentlessly and it is another source of discontent (Diaz-Parra & Jover, 2020). In sum over-touristification leads to many negative externalities, but the same effects in the rural context can really improve the quality of life of communities that are slowly dying from both demographic and economic points of view (Battino & Lampreu, 2019; Hernández-Maestro & González-Benito, 2014; Strømmen-Bakhtiar et al., 2020).

The thesis supports the disruptive innovation effect from digital accommodation platforms towards the incumbent in the market, the hotels (Guttentag, 2015). Furthermore, the empirical evidence seems to suggest which are the categories mostly affected by the substitution effect: in the examined context the digital accommodation platform solutions apparently substitute the hotels located outside of city centres, not being able to impact significantly on the hotels located inside city centres. Digital accommodation platforms could play the role of disruptor in rural villages as well, not against existing hotels but against potential future hotels. In other words, being the digital accommodation platforms quicker and easier to set-up (Hernández-Maestro & González-Benito, 2014; Thirumalesh Madanaguli et al., 2021), they could be able to saturate potential touristic accommodation of a destination, making unprofitable for a hotel to invest in a certain location.

The empirical evidence analysed does not recognize as significantly useful the presence of good online reputation and visibility to improve hotels and destinations performances. From one side this may come at surprise, with previous literature extensively underlining the importance of online reputation and visibility in accommodation (Hollenbeck, 2018; Perez-Aranda, Vallespín, & Molinillo, 2019; Schuckert et al., 2015), but on the other side this results agree with a more recent literature stream that is observing a decreasing discriminating power of online rating and presence (Schoenmueller et al., 2018). In the context of this thesis both online reputation and visibility have scarce variability, meaning low discriminating power. This may be also related with the overwhelming quantity of information everyone is exposed daily and to the limited amount of trust we give to people we don't know.

The thesis supports the idea that touristic destinations relies on networked core-competencies in becoming attractive, being aware of this or not (Denicolai et al., 2010). The resources and the competencies made possible by the digital accommodation platforms (Airbnb in particular, which dedicated some effort towards Italian rural destinations) play in fact a fundamental role in the touristic development of the rural destinations taken into consideration. The relationships among tourism entities are so intense because they all depends from the same person to survive: the tourist. Previously rural communities needed to convince a big investor to build a touristic accommodation structure to have this resource, while now it is possible to spread the risk and the cost among a lot of components of the community. At the same time digital accommodation platforms are also an intermediary for the destination accommodation solutions to reach the potential tourists. For these reasons digital accommodation platforms could really empower rural touristic destination to improve their wealth.

5.2.1 Managerial implications

The results and the observations in this thesis are also aimed at readers out of academia, in this sections are collected the main suggestions for managers in hospitality sector and policy makers dealing with tourism. Given the possibilities that digital accommodation platforms open to under evaluated touristic destinations, hotels groups decision makers should follow quickly and closely the diffusion of digital accommodation platforms solutions because they may act as indicators of future touristically attractive areas. When communities are involved and benefit from the development of some areas the potential attractiveness should increase much faster. Hotels should also consider the possibility of adapting their capability in offering hospitality services to rural destination context, main example of this being the phenomenon of "Alberghi diffusi" (https://www.alberghidiffusi.it/?lang=en).

Hotels group decision makers should also reconsider the relationship with touristic assets in terms of distance to them. In fact, in the thesis the short distance to main touristic attractions is protecting the profit of hotels. This fact reflects the necessity of most travellers to save precious time in reaching their destinations. New investments in hotels should consider this as of primary importance. Hotels already existing should consider the touristic attraction they have in the surrounding area and leverage them to attract their customers.

5.3 Future effect of artificial intelligence diffusion

In the introduction of conclusion chapter, the thesis presents the outcomes of the second part of this dissertation. The artificial intelligence domains of application more interesting from the point of view of the market are: Services, Learning and Communication. These three technological domains aim at the automation of customer service and relationship management and marketing intelligence, enlarging the scale of the companies and allowing them to generate insights from a larger amount of data in a more efficient manner. The results of this thesis suggest that artificial intelligence will be exploited to collect even more data about customers and potential customers in order to create smaller segments or even customize offer client by client optimizing revenue generation and cross selling opportunities.

Moreover, the phases of the supply chain more interesting from the point of view of the market are the pre-trip phase (composed by Trip inspiration and Booking and preparation) and the post-trip phase. The market attributes more value to artificial intelligence technologies when used as a way to track and understand the tourists when they are not travelling. In fact, the start-ups based on a business model that targets Travel services and Destination services are fewer and less financed, meaning the market believes these jobs are less likely to be substituted by artificial intelligence systems. Many start-ups operate both in pre-trip phase and post-trip phase, meaning they are trying to track tourists between a trip and the next one, influencing it choice. The evidence collected in the thesis suggests that the supply chain is becoming less linear and more circular from the perspective of the tourist. In other words, since without technological support there were no active ways to influence customers' choices before they start the process of looking for a destination, the supply chain used to develop in a linear way every time the tourists started the interaction with tourism industry. Now it is possible to reach and track the tourists, starting to influence their choices just after they finished a trip, without a break between two interactions. Finally, most analysed start-ups are specialised on a single phase of the tourism supply chain, meaning there is an effort to leverage specific competencies and knowledge.

This dissertation concludes with an attempt to speculate about how the innovation analysed in Chapter 4 could spread, based on author's experience. Given the structure of tourism industry, characterised by the presence of few very big players and a multitude of hyper-fragmented entities (Weiermair & Kronenberg, 2004), this thesis suggests there will be two main ways for the start-ups to spread the innovation based on artificial intelligence they are developing: being acquired by one of the incumbents, like an hotel chain or an airline, or starting to target the hyper-fragmented multitude of small companies like independent hotels or travel agencies. The main digital platforms in this industry could also play a role in developing innovation, but given their big size and their young age and digital mind-set we expect this innovation will be mostly internally developed. For example, Airbnb is heavily applying artificial intelligence solutions to its internal processes in order to test it (Iansiti & Lakhani, 2020). Moreover, we may expect that tourism companies and organisations operating in countries where start-ups are flourishing will probably benefit the most from AI solutions since they will benefit of the "regional advantage" of concentration of knowledge and capabilities where they are already developed (R. Martin & Sunley, 2006; Saxenian, 1996).

5.4 Limitations and future research

Although this thesis provides more than one research contribution to the circumstances under which digital accommodation platforms impacts on existing companies and societies and to the way tourism industry will evolve from a structural point of view, it suffers from some limitations that may be addressed in future research. One main limitation for sure is the generalizability of the obtained results in different context in terms of geography, industry and type of companies. The choice of specific geographical areas helped us in fixing homogeneous characteristics for the empirical framework without the need to worry about many factors that may change but of course the results are replicable only in areas with similar characteristics. The same goes also regarding the choice of the set to be analysed.

A second limitation of the thesis is the narrow number of moderating variables put under testing. Unfortunately, even if the literature supplies many useful inspirations about moderators that could influence the general relationship between digital accommodation platforms and existing companies and societies it is not possible to test them all, we hope this thesis could serve as inspiration for other researchers to continue this work of disentangling general theories application to specific contexts.

As a last limitation there is the possibility that the application of a theory in a context different from the original could misrepresent it, leading to distort interpretations.

References

Acs, Z. J., Song, A. K., Szerb, L., Audretsch, D. B., & Komlósi, É. (2021). The evolution of the global digital platform economy: 1971–2021. *Small Business Economics*, *57*(4), 1629–1659. https://doi.org/10.1007/s11187-021-00561-x

Adenwala, M. (2014). *IMPACT OF E-COMMERCE ON BUSINESS PERFORMANCE: A STUDY WITH RESPECT TO TRAVEL INDUSTRY Dissertation Submitted to the*. *Master of Philosophy in Business management*. Retrieved from http://www.dypatil.edu/schools/management/wp-content/uploads/2015/05/IMPACT-OF-E-COMMERCE-ON-BUSINESS-PERFORMANCE-A-STUDY-WITH-RESPECT-TO-TRAVEL-INDUSTRY-Murtaza-Adenwala.pdf

Airbnb. (2019). Airbnb Newsroom. Retrieved from https://news.airbnb.com/about-us/

Akbar, Y. H., & Tracogna, A. (2018). The sharing economy and the future of the hotel industry: Transaction cost theory and platform economics. *International Journal of Hospitality Management*, *71*(October 2017), 91–101. https://doi.org/10.1016/j.ijhm.2017.12.004

Aleksandrov, I., & Fedorova, M. (2018). Strategic planning of the tourism development in small cities and rural territories as a tool for the development of the regional economy. *MATEC Web of Conferences*, *170*. https://doi.org/10.1051/matecconf/201817001011

Anderson, E. W., & Sullivan, M. W. (1993). The Antecedents and Consequences of Customer Satisfaction for Firms. *Marketing Science*, *12*(2), 125–143. https://doi.org/10.1287/mksc.12.2.125

Armour, J., & Sako, M. (2020). AI-enabled business models in legal services: From traditional law firms to next-generation law companies? *Journal of Professions and Organization*, *7*(1), 27–46. https://doi.org/10.1093/jpo/joaa001

Arthurs, J., & Busenitz, L. (2006). Dynamic Capabilities and Venture Performance:

The Effects of Venture Capitalists. *Journal of Business Venturing*, *21*, 195–215. https://doi.org/https://doi.org/10.1016/j.jbusvent.2005.04.004

Aznar, J. P., Sayeras, J. M., Rocafort, A., & Galiana, J. (2017). The irruption of Airbnb and its effects on hotel profitability: An analysis of Barcelona's hotel sector. *Intangible Capital*, *13*(1), 147–159. https://doi.org/http://dx.doi.org/10.3926/ic.921

Baden-Fuller, C., & Mangematin, V. (2012). Business models: A challenging agenda. *Strategic Organization*, *11*(4), 418–427. https://doi.org/10.1177/1476127013510112

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1016/S0742-3322(00)17018-4

Barney, J. B. (1986). Strategic Factor Markets: Expectations, Luck, and Business Strategy. *Management Science*, *32*(10), 1231–1241. https://doi.org/10.1287/mnsc.32.10.1231

Battino, S., & Lampreu, S. (2019). The role of the sharing economy for a sustainable and innovative development of rural areas: A case study in Sardinia (Italy). *Sustainability (Switzerland)*, *11*(11). https://doi.org/10.3390/su11113004

Baum, J. A. C., & Haveman, H. A. (1997). Love thy neighbor? Differentiation and agglomeration in the Manhattan hotel industry, 1898-1990. *Administrative Science Quarterly*, *42*(2), 304–338. https://doi.org/10.2307/2393922

Becerra, M., Santaló, J., & Silva, R. (2013). Being better vs. being different: Differentiation, competition, and pricing strategies in the Spanish hotel industry. *Tourism Management*, *34*, 71–79. https://doi.org/10.1016/j.tourman.2012.03.014

Bekar, C., Carlaw, K., & Lipsey, R. (2018). General purpose technologies in theory, application and controversy: a review. *Journal of Evolutionary Economics*, *28*(5), 1005–1033. https://doi.org/10.1007/s00191-017-0546-0

Belanche, D., Casaló, L. V., & Flavián, C. (2020). Frontline robots in tourism and hospitality: service enhancement or cost reduction? *Electronic Markets*, (July). https://doi.org/10.1007/s12525-020-00432-5

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020a). Robots or frontline employees? Exploring customers' attributions of responsibility and stability after service failure or success. *Journal of Service Management*, *31*(2), 267–289. https://doi.org/https://doi.org/10.1108/JOSM-05-2019-0156

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020b). Service robot implementation: a theoretical framework and research agenda. *The Service Industries Journal*, *40*(3–4), 203–225. https://doi.org/https://doi.org/10.1080/02642069.2019.1672666

Benckendorff, P., Xiang, Z., & Sheldon, P. (2019). *Tourism Information Technology* (3rd ed.). CABI Publishing. Retrieved from https://www.cabi.org/bookshop/book/9781786393432/

Bethapudi, A. (2013). The role of ICT In tourism industry. *Journal of Applied Economics and Business*, *1*(4), 67–79. Retrieved from http://www.aebjournal.org/articles/0104/010406.pdf

Blal, I., Singal, M., & Templin, J. (2018). Airbnb's effect on hotel sales growth. *International Journal of Hospitality Management*, *73*(February), 85–92. https://doi.org/10.1016/j.ijhm.2018.02.006

Bolzani, D., Fini, R., Napolitano, S., & Toschi, L. (n.d.). Entrepreneurial Teams : An Input-Process-Outcome Framework, *15*(2), 56–258. https://doi.org/10.1561/0300000077.The

Bosworth, G., & Farrell, H. (2011). Tourism entrepreneurs in Northumberland. *Annals of Tourism Research*, *38*(4), 1474–1494. https://doi.org/https://doi.org/10.1016/j.annals.2011.03.015

Bower, J. L., & Christensen, C. M. (1995). Disruptive technologies: catching the wave. *Harvard Business Reivew*, *28*(2), 155. https://doi.org/10.1016/0024-6301(95)91075-1

Brandenburger, A. M., & Nalebuff, B. J. (1996). *Co-Opetition*. New York, NY: Doubleday. Retrieved from https://books.google.it/books?hl=it&lr=&id=sU2e-piQ3tUC&oi=fnd&pg=PA3&ots=OdE1aMMOpm&sig=gNgY-9cnC7hKZgOSanFveNgT_e8&redir_esc=y#v=onepage&q&f=false

Bredvold, R., & Skålén, P. (2016). Lifestyle entrepreneurs and their identity construction: A study of the tourism industry. *Tourism Management*, *56*, 96–105. https://doi.org/https://doi.org/10.1016/j.tourman.2016.03.023

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies "Engines of growth"? *Journal of Econometrics*, *65*(1), 83–108. https://doi.org/10.1016/0304-4076(94)01598-T

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: work, progress, and prosperity in a time of brilliant technologies* (First edit). Retrieved from https://catalog.hathitrust.org/Record/102324801

Brynjolfsson, E., McAfee, A., Sorell, M., & Zhu, F. (2008). Scale Without Mass: Business Process Replication and Industry Dynamics. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.980568

Brynjolfsson, E., Rock, D., & Syverson, C. (2017). *Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics* (NBER Working Paper Series No. 24001). *NBER Working Paper*. https://doi.org/10.3386/w24001

Brzezińska-Wójcik, T., & Skowronek, E. (2020). Tangible Heritage of the Historical Stonework Centre in Brusno Stare in the Roztocze Area (SE Poland) as an Opportunity for the Development of Geotourism. *Geoheritage*, *12*(1). https://doi.org/10.1007/s12371-020-00442-x

Buhalis, D., Harwood, T., Bogicevic, V., Viglia, G., Beldona, S., & Hofacker, C. (2019). Technological disruptions in Services: lessons from Tourism and Hospitality. *Journal of Service Management*, *30*(4), 484–506. https://doi.org/https://doi.org/10.1108/JOSM-12-2018-0398

Buhalis, D., & Sinarta, Y. (2019). Real-time co-creation and nowness service: lessons from tourism and hospitality. *Journal of Travel and Tourism Marketing*, *36*(5), 563–582. https://doi.org/https://doi.org/10.1080/10548408.2019.1592059

Buhalis, D., & Spada, A. (2000). Destination Management Systems: Criteria for Success — An Exploratory Research. *Information and Communication Technologies in Tourism 2000*, 473–484. https://doi.org/10.1007/978-3-7091-6291-0_43

Burtch, G., Carnahan, S., & Greenwood, B. N. (2018). Can you gig it? an empirical examination of the gig economy and entrepreneurial activity. *Management Science*, (March), 5497–5520. https://doi.org/10.1287/mnsc.2017.2916

Camuffo, A., Cordova, A., Gambardella, A., & Spina, C. (2019). A scientific approach to entrepreneurial decision making: Evidence from a randomized control trial. *Management Science*, *66*(2), 564–586. https://doi.org/https://doi.org/10.1287/mnsc.2018.3249

Chalmers, D., MacKenzie, N. G., & Carter, S. (2020). Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution. *Entrepreneurship: Theory and Practice*, 1–26. https://doi.org/https://doi.org/10.1177/1042258720934581

Chan Kim, W., & Mauborgne, R. (2005). *Blue Ocean Strategy: How to Create Uncontested Market Space and Make the Competition Irrelevant* (Harvard Bu). Boston, MA: Harvard Business School Press. https://doi.org/10.1016/j.lrp.2008.02.003

Chatterji, A., Delecourt, S., Hasan, S., & Koning, R. (2019). When does advice impact startup performance? *Strategic Management Journal*, *40*(3), 331–356. https://doi.org/https://doi.org/10.1002/smj.2987

Chatterji, A., Delecourt, S., Hasan, S., & Koning4, R. (2017). When does advice impact startup performance? *Strategic Management Journal*.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data To Big Impact. *MIS Quarterly*, *36*(4), 1165–1188. https://doi.org/http://dx.doi.org/10.2307/41703503

Choi, K.-H., Jung, J., Ryu, S., Kim, S.-D., & Yoon, S.-M. (2015). The Relationship between Airbnb and the Hotel Revenue: In the Case of Korea. *Indian Journal of Science and Technology*, *8*(26). https://doi.org/10.17485/ijst/2015/v8i26/81013

Christensen, C. M. (1997). *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. *Harvard Business School Press*. Boston, Massachusetts: Harvard Business School Press.

Christensen, C. M., & Raynor, M. E. (2003). *The Innovator's Solution: Creating and Sustaining Successful Growth*. Harvard Business Review Press.

Chu, R. K. S., & Choi, T. (2000). An importance-performance analysis of hotel selection factors in the Hong Kong hotel industry: A comparison of business and leisure travellers. *Tourism Management*, *21*(4), 363–377. https://doi.org/10.1016/S0261-5177(99)00070-9

Clarke, G. R. G., Qiang, C. Z., & Xu, L. C. (2015). The Internet as a general-purpose technology: Firm-level evidence from around the world. *Economics Letters*, *135*, 24–27. https://doi.org/10.1016/j.econlet.2015.07.004

Constantinides, P., Henfridsson, O., & Parker, G. G. (2018). Platforms and infrastructures in the digital age. *Information Systems Research*, *29*(2), 381–400. https://doi.org/10.1287/isre.2018.0794

Coombs, C., Stacey, P., Kawalek, P., Simeonova, B., Becker, J., Bergener, K., … Trautmann, H. (2021). What is it about humanity that we can't give away to intelligent machines? A European perspective. *International Journal of Information Management*, *58*.

https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2021.102311

Crafts, N. (2021). Artificial intelligence as a general-purpose technology: an historical perspective. *Oxford Review of Economic Policy*, *37*(3), 521–536. https://doi.org/10.1093/oxrep/grab012

Daft, R. L. (1983). *Organization Theory and Design*. New York, NY: West Pub. Co.

Dahl, M. S., & Sorenson, O. (2012). Home sweet home: Entrepreneurs' location choices and the performance of their ventures. *Management Science*, *58*(6), 1059–1071. https://doi.org/https://doi.org/10.1287/mnsc.1110.1476

Dann, D., Teubner, T., & Weinhardt, C. (2019). Poster child and guinea pig – insights from a structured literature review on Airbnb. *International Journal of Contemporary Hospitality Management*, *31*(1), 427–473. https://doi.org/10.1108/IJCHM-03-2018-0186

Davidsson, P., & Honig, B. (2003). The role of social and human capital among nascent entrepreneurs. *Journal of Business Venturing*, *18*(3), 301–331. https://doi.org/https://doi.org/10.1016/S0883-9026%2802%2900097-6

Davies, A., & Lahiri, K. (1995). A new framework for analyzing survey forecasts using three-dimensional panel data. *Journal of Econometrics*, *68*(1), 205–227. https://doi.org/10.1016/0304-4076(94)01649-K

de Kervenoael, R., Hasan, R., Schwob, A., & Goh, E. (2020). Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions to use social robots. *Tourism Management*, *78*(November), 104042. https://doi.org/https://doi.org/10.1016/j.tourman.2019.104042

Debbage, K. G., & Ioannides, D. (1998). *The Economic Geography of the Tourist Industry A Supply-Side Analysis*. Routledge. Retrieved from https://www.routledge.com/The-Economic-Geography-of-the-Tourist-Industry-A-Supply-Side-Analysis/Debbage-Ioannides/p/book/9780415164122

Debreceny, R. S., Wang, T., & Zhou, M. J. (2019). Research in social media: Data sources and methodologies. *Journal of Information Systems*, *33*(1), 1–28. https://doi.org/https://doi.org/10.2308/isys-51984

Denicolai, S., Cioccarelli, G., & Zucchella, A. (2010). Resource-based local development and networked core-competencies for tourism excellence. *Tourism Management*, *31*(2), 260–266.

https://doi.org/10.1016/j.tourman.2009.03.002

Destefanis, A., Neirotti, P., Paolucci, E., & Raguseo, E. (2020). The impact of Airbnb on the economic performance of independent hotels: an empirical investigation of the moderating effects. *Current Issues in Tourism*, 1–31. https://doi.org/10.1080/13683500.2020.1846501

Diaz-Parra, I., & Jover, J. (2020). Overtourism, place alienation and the right to the city: insights from the historic centre of Seville, Spain. *Journal of Sustainable Tourism*, *0*(0), 1–18. https://doi.org/10.1080/09669582.2020.1717504

Ditta-Apichai, M., Kattiyapornpong, U., & Gretzel, U. (2020). Platform-mediated tourism micro-entrepreneurship: implications for community-based tourism in Thailand. *Journal of Hospitality and Tourism Technology*, *11*(2), 223–240. https://doi.org/10.1108/JHTT-05-2019-0079

Dogru, T., Mody, M., & Suess, C. (2019). Adding evidence to the debate : Quantifying Airbnb ' s disruptive impact on ten key hotel markets. *Tourism Management*, *72*(June 2018), 27–38. https://doi.org/10.1016/j.tourman.2018.11.008

Dogru, T., Mody, M., Suess, C., McGinley, S., & Line, N. D. (2020). The Airbnb paradox: Positive employment effects in the hospitality industry. *Tourism Management*, *77*(March 2019), 104001. https://doi.org/10.1016/j.tourman.2019.104001

Dolnicar, S., & Otter, T. (2003). Which Hotel attributes Matter ? A review of previous and a framework for future research. *Proceedings of the 9th Annual Conference of the Asia Pacific Tourism Association (APTA)*, (January), 176–188. https://doi.org/http://ro.uow.edu.au/commpapers/268

Doz, Y. L., & Hamel, G. (1998). *Alliance Advantage: The Art of Creating Value Through Partnering*. Harvard Business School Press. Retrieved from https://www.abebooks.it/9780875846163/Alliance-Advantage-Art-Creating-Value-0875846165/plp

Eckert, R. (2019). *Disruptive Business Imitation – Neun Beschleuniger zum kreativen Imitieren disruptiver Geschäftsmodelle*. *Springer-Verlag, 2018*. Springer-Verlag, 2018. https://doi.org/10.1007/978-3-658-24702-7_3

Egan, D. J., & Nield, K. (2000). Towards a theory of intraurban hotel location. *Urban Studies*, *37*(3), 611–621. https://doi.org/10.1080/0042098002140

Elia, G., Margherita, A., & Passiante, G. (2020). Digital entrepreneurship ecosystem: How digital technologies and collective intelligence are reshaping the entrepreneurial process. *Technological Forecasting and Social Change*, *150*(January 2019), 119791. https://doi.org/https://doi.org/10.1016/j.techfore.2019.119791

Ert, E., & Fleischer, A. (2019). The evolution of trust in Airbnb: A case of home rental. *Annals of Tourism Research*. https://doi.org/10.1016/j.annals.2019.01.004

Espino-Rodriguez, T. F., & Padrón-Robaina, V. (2006). A review of outsourcing from the resource-based view of the firm. *International Journal of Management Reviews*, *8*(1), 49–70. https://doi.org/10.1111/j.1468-2370.2006.00120.x

Evans, D. S., & Schmalensee, R. (2016). *Matchmakers : the new economics of multisided platforms*. Boston, Massachusetts: Harvard Business Review Press.

Filieri, R., D'Amico, E., Destefanis, A., Paolucci, E., & Raguseo, E. (2021). Artificial intelligence (AI) for tourism: an European-based study on successful AI tourism start-ups. *International Journal of Contemporary Hospitality Management*. https://doi.org/10.1108/IJCHM-02-2021-0220

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2021). Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness. *Journal of Service Management*. https://doi.org/10.1108/JOSM-10-2020-0378

Fong, V. H. I., Hong, J. F. L., & Wong, I. K. A. (2021). The evolution of triadic relationships in a tourism supply chain through coopetition. *Tourism Management*, *84*(October 2020), 104274. https://doi.org/https://doi.org/10.1016/j.tourman.2020.104274

Forgacs, G., & Dimanche, F. (2016). Revenue challenges for hotels in the sharing economy: Facing the Airbnb menace. *Journal of Revenue and Pricing Management*, *15*(6), 509–515. https://doi.org/10.1057/s41272-016-0071-z

Franke, M. (2004). Competition between network carriers and low-cost carriers - Retreat battle or breakthrough to a new level of efficiency? *Journal of Air Transport Management*, *10*(1), 15–21. https://doi.org/10.1016/j.jairtraman.2003.10.008

Frei, F. X. (2006). Breaking the trade-off between efficiency and service. *Harvard Business Review*, *84*(11).

Frenken, K., & Schor, J. (2017). Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions*, *23*, 3–10.

https://doi.org/10.1016/j.eist.2017.01.003

Fu, H., Okumus, F., Wu, K., & Köseoglu, M. A. (2019). The entrepreneurship research in hospitality and tourism. *International Journal of Hospitality Management*, *78*(October 2018), 1–12. https://doi.org/https://doi.org/10.1016/j.ijhm.2018.10.005

Garrido-Moreno, A., García-Morales, V. J., Lockett, N., & King, S. (2018). The missing link: Creating value with Social Media use in hotels. *International Journal of Hospitality Management*, *75*, 94–104. https://doi.org/10.1016/j.ijhm.2018.03.008

Getz, D., & Peterson, T. (2005). Growth and profit-oriented entrepreneurship among family business owners in the tourism and hospitality industry. *International Journal of Hospitality Management*, *24*(2), 219–242. https://doi.org/https://doi.org/10.1016/j.ijhm.2004.06.007

Ginindza, S., & Tichaawa, T. M. (2017). The impact of sharing accommodation on the hotel occupancy rate in the kingdom of Swaziland. *Current Issues in Tourism*, *0*(0), 1–17. https://doi.org/10.1080/13683500.2017.1408061

Glancey, K., & Pettigrew, M. (1997). Entrepreneurship in the small hotel sector. *International Journal of Contemporary Hospitality Management*, *9*(1), 21–24. https://doi.org/10.1108/09596119710157540

González-Pérez, J. M. (2020). The dispute over tourist cities. Tourism gentrification in the historic Centre of Palma (Majorca, Spain). *Tourism Geographies*, *22*(1), 171–191. https://doi.org/10.1080/14616688.2019.1586986

Greene, W. H. (2003). *ECONOMETRIC ANALYSIS* (5th editio). New Jersey: Prentice Hall.

Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: foundations and developments. *Electronic Markets*, *25*(3), 179–188. https://doi.org/https://doi.org/10.1007/s12525-015-0196-8

Groen, A. J., Wakkee, I. A. M., & De Weerd-Nederhof, P. C. (2008). Managing tensions in a high-tech start-up: An innovation journey in social system perspective. *International Small Business Journal*, *26*(1), 57–81. https://doi.org/https://doi.org/10.1177/0266242607084659

Grosz, B. J., Altman, R., Horvitz, E., Mackworth, A., Mitchell, T., Mulligan, D., & Shoham, Y. (2016). Artificial intelligence and life in 2030: One hundred year study on artificial intelligence.

Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, *18*(12), 1192–1217. https://doi.org/10.1080/13683500.2013.827159

Guttentag, D., & Smith, S. L. J. (2017). Assessing Airbnb as a disruptive innovation relative to hotels: Substitution and comparative performance expectations. *International Journal of Hospitality Management*, *64*, 1–10. https://doi.org/10.1016/j.ijhm.2017.02.003

Guzman, J., & Kacperczyk, A. (Olenka). (2019). Gender gap in entrepreneurship. *Research Policy*, *48*(7), 1666–1680. https://doi.org/https://doi.org/10.1016/j.respol.2019.03.012

Hallak, R., Assaker, G., & Lee, C. (2015). Tourism Entrepreneurship Performance: The Effects of Place Identity, Self-Efficacy, and Gender. *Journal of Travel Research*, *54*(1), 36–51. https://doi.org/https://doi.org/10.1177/0047287513513170

Hallak, R., Brown, G., & Lindsay, N. J. (2012). The Place Identity - Performance relationship among tourism entrepreneurs: A structural equation modelling analysis. *Tourism Management*, *33*(1), 143–154. https://doi.org/https://doi.org/10.1016/j.tourman.2011.02.013

Hallin, C. A., & Marnburg, E. (2008). Knowledge management in the hospitality industry: A review of empirical research. *Tourism Management*, *29*(2), 366–381. https://doi.org/10.1016/j.tourman.2007.02.019

Hamari, J., Sjöklint, M., & Ukkonen, A. (2015). The Sharing Economy: Why People Participate in Collaborative Consumption. *Journal of the American Society for Information Science and Technology*, *67*(9), 2047–2059. https://doi.org/10.1002/asi.23552

Hamel, G. (2002). *Leading the Revolution: How to Thrive in Turbulent Times by Making Innovation a Way of Life*. New York, NY: Harvard Business School Press.

Hansen Henten, A., & Maria Windekilde, I. (2016). Transaction costs and the sharing economy. *INFO*, *18*(1), 1–15. https://doi.org/10.1108/info-09-2015-0044

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica*, *46*(6), 1251. https://doi.org/10.2307/1913827

Hernández-Maestro, R. M., & González-Benito, Ó. (2014). Rural Lodging Establishments as Drivers of Rural Development. *Journal of Travel Research*, *53*(1), 83–95. https://doi.org/https://doi.org/10.1177/0047287513481273

Hilbert, M., & López, P. (2011). The world's technological capacity to store, communicate, and compute information. *Science*, *332*(60), 60–65. https://doi.org/10.1126/science.1200970

Hollenbeck, B. (2018). Online reputation mechanisms and the decreasing value of chain affiliation. *Journal of Marketing Research*, *55*(5), 636–654. https://doi.org/10.1177/0022243718802844

Hoogendoorn, S., Oosterbeek, H., & Van Praag, M. (2013). The impact of gender diversity on the performance of business teams: Evidence from a field experiment. *Management Science*, *59*(7), 1514–1528. https://doi.org/https://doi.org/10.1287/mnsc.1120.1674

Huang, J. C., Henfridsson, Ola, Liu, M. J., & Newell, S. (1999). Growing on steroids: rapidly scaling the user base of digital ventures through digital innovation. *MIS Quarterly*, *41*(1), 301–314. https://doi.org/10.25300/MISQ/2017/41.1.16

Iansiti, M., & Lakhani, K. R. (2020). *Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World*. Harvard Business School Press.

Ivanov, S., & Webster, C. (2019a). Conceptual framework of the use of robots, artificial intelligence and service automation in travel, tourism, and hospitality companies. In *Robots, Artificial Intelligence and Service Automation in Travel, Tourism and Hospitality* (pp. 7–37). Retrieved from https://www.emerald.com/insight/content/doi/10.1108/978-1-78756-687-320191001/full/html

Ivanov, S., & Webster, C. (2019b). Economic fundamentals of the use of robots, artifiial intelligence, and service automation in travel, tourism, and hospitality. In *Robots, Artificial Intelligence and Service Automation in Travel, Tourism and Hospitality* (pp. 39–55). Retrieved from https://www.emerald.com/insight/content/doi/10.1108/978-1-78756-687-320191001/full/html

Jo, H., & Lee, J. (1996). The relationship between an entrepreneur's background and performance in a new venture. *Technovation*, *16*(4), 161–171. https://doi.org/10.1016/0166-4972(96)89124-3

Johnson, A. G., & Neuhofer, B. (2017). Airbnb – an exploration of value co-creation experiences in Jamaica. *International Journal of Contemporary Hospitality Management*, *29*(9), 2361–2376. https://doi.org/10.1108/IJCHM-

08-2016-0482

Jovanovic, B., & Rousseau, P. L. (2005). General Purpose Technologies. In *Handbook of Economic Growth* (Vol. 1, pp. 1181–1224). Elsevier Masson SAS. https://doi.org/10.1016/S1574-0684(05)01018-X

Kallmuenzer, A., Kraus, S., Peters, M., Steiner, J., & Cheng, C. F. (2019). Entrepreneurship in tourism firms: A mixed-methods analysis of performance driver configurations. *Tourism Management*, *74*(August 2018), 319–330. https://doi.org/https://doi.org/10.1016/j.tourman.2019.04.002

Kandampully, J. (2006). The new customer-centred business model for the hospitality industry. *International Journal of Contemporary Hospitality Management*, *18*(3), 173–187. https://doi.org/10.1108/09596110610658599

Karimi, J., & Walter, Z. (2015). The role of dynamic capabilities in responding to digital disruption: A factor-based study of the newspaper industry. *Journal of Management Information Systems*, *32*(1), 39–81. https://doi.org/10.1080/07421222.2015.1029380

Katsinas, P. (2021). Professionalisation of short-term rentals and emergent tourism gentrification in post-crisis Thessaloniki. *Environment and Planning A*, *0*(May 2018), 1–19. https://doi.org/10.1177/0308518X21988940

Katz, R., Koutroumpis, P., & Callorda, F. M. (2014). Using a digitization index to measure the economic and social impact of digital agendas. *Info*, *16*(1), 32–44. https://doi.org/10.1108/info-10-2013-0051

Kazak, A. N., Chetyrbok, P. V., & Oleinikov, N. N. (2020). Artificial intelligence in the tourism sphere. *IOP Conference Series: Earth and Environmental Science*, *421*(4). https://doi.org/10.1088/1755-1315/421/4/042020

Kenney, M., & Zysman, J. (2016). The Rise of the Platform Economy. Issues in Science and Technology. *Issues in Science and Technology*, *Spring*, 61–69.

Kim, H. J., Kim, T. S., & Sohn, S. Y. (2020). Recommendation of startups as technology cooperation candidates from the perspectives of similarity and potential: A deep learning approach. *Decision Support Systems*, *130*. https://doi.org/https://doi.org/10.1016/j.dss.2019.113229

Kivell, P. (1993). *Land and the city*. London: Routledge.

Klinger, J., Mateos-Garcia, J. C., & Stathoulopoulos, K. (2018). Deep Learning, Deep Change? Mapping the Development of the Artificial Intelligence General Purpose Technology. *SSRN Electronic Journal*.

https://doi.org/10.2139/ssrn.3233463

Ko, E.-J., & McKelvie, A. (2018). Signaling for more money: The roles of founders' human capital and investor prominence in resource acquisition across different stages of firm development. *Journal of Business Venturing*, *33*(4), 438–454. https://doi.org/https://doi.org/10.1016/j.jbusvent.2018.03.001

Koh, E., & King, B. (2017). Accommodating the sharing revolution: a qualitative evaluation of the impact of Airbnb on Singapore's budget hotels. *Tourism Recreation Research*, *42*(4), 409–421. https://doi.org/10.1080/02508281.2017.1314413

Kotas, R. (1982). The European hotel: methodology for analysis of financial operations and identification of appropriate business strategy. *International Journal of Hospitality Management*, *1*(2), 79–84. https://doi.org/10.1016/0278-4319(82)90037-8

Kraus, S., Palmer, C., Kailer, N., Kallinger, F. L., & Spitzer, J. (2019). Digital entrepreneurship: A research agenda on new business models for the twenty-first century. *International Journal of Entrepreneurial Behaviour and Research*, *25*(2), 353–375. https://doi.org/https://doi.org/10.1108/IJEBR-06-2018-0425

Lado-Sestayo, R., Vivel-Búa, M., & Otero-González, L. (2020). Connection between hotel location and profitability drivers: an analysis of location-specific effects. *Current Issues in Tourism*, *23*(4), 452–469. https://doi.org/10.1080/13683500.2018.1538203

Lahuerta Otero, E., Muñoz Gallego, P. A., & Pratt, R. M. E. (2014). Click-and-Mortar SMEs: Attracting customers to your website. *Business Horizons*, *57*(6), 729–736. https://doi.org/10.1016/j.bushor.2014.07.006

Lechler, T. (2001). Social Interaction: A Determinant of Entrepreneurial Team Venture Success. *Small Business Economics*, *16*(4), 263–278. https://doi.org/https://doi.org/10.1023/A:1011167519304

Lee, K., & Yuan, J. (2017). Hospitality and tourism Industry Segments: Towards a New Taxonomy. *E-Review of Tourism Research*, *14*(1), 37–56. Retrieved from https://journals.tdl.org/ertr/index.php/ertr/article/view/86/8

Lee, S. G., Trimi, S., & Kim, C. (2013). Innovation and imitation effects' dynamics in technology adoption. *Industrial Management & Data Systems*, *113*(6), 772–799. https://doi.org/10.1108/IMDS-02-2013-0065

Lee, S. K., & Jang, S. C. S. (2012). Re-examining the overcapacity of the US lodging industry. *International Journal of Hospitality Management*, *31*(4), 1050–1058. https://doi.org/10.1016/j.ijhm.2012.01.001

Lehto, X. Y., Park, O. J., & Gordon, S. E. (2015). Migrating to New Hotels: A Comparison of Antecedents of Business and Leisure Travelers' Hotel Switching Intentions. *Journal of Quality Assurance in Hospitality and Tourism*, *16*(3), 235–258. https://doi.org/10.1080/1528008X.2014.925787

Leone, D., Schiavone, F., Appio, F. P., & Chiao, B. (2020). How does artificial intelligence enable and enhance value co-creation in industrial markets? An exploratory case study in the healthcare ecosystem. *Journal of Business Research*. https://doi.org/https://doi.org/10.1016/j.jbusres.2020.11.008

Li, H., & Srinivasan, K. (2019). Competitive Dynamics in the Sharing Economy: An Analysis in the Context of Airbnb and Hotels. *Marketing Science*, (June), mksc.2018.1143. https://doi.org/10.1287/mksc.2018.1143

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, *29*(3), 458–468. https://doi.org/10.1016/j.tourman.2007.05.011

Lu, H., Li, Y., Chen, M., Kim, H., & Serikawa, S. (2018). Brain Intelligence: Go beyond Artificial Intelligence. *Mobile Networks and Applications*, *23*(2), 368–375. https://doi.org/https://doi.org/10.1007/s11036-017-0932-8

Lyytinen, K., Yoo, Y., & Boland, R. J. (2016). Digital product innovation within four classes of innovation networks. *Information Systems Journal*, *26*(1), 47–75. https://doi.org/10.1111/isj.12093

Maggioni, I., Marcoz, E. M., & Mauri, C. (2014). Segmenting networking orientation in the hospitality industry: An empirical research on service bundling. *International Journal of Hospitality Management*, *42*, 192–201. https://doi.org/10.1016/j.ijhm.2014.07.002

Marios Sotiriadis, C. V. Z. (2017). SHARING ECONOMY IN THE HOSPITALITY INDUSTRY: ANALYSIS, SUGGESTED STRATEGIES AND AVENUES FOR FUTURE RESEARCH. *TOURISMOS*, *12*(1), 144–165.

Markides, C. (2006). Disruptive innovation: In need of better theory. *Journal of Product Innovation Management*, *23*(1), 19–25. https://doi.org/10.1111/j.1540-5885.2005.00177.x

Martin, B. C., McNally, J. J., & Kay, M. J. (2013). Examining the formation of human capital in entrepreneurship: A meta-analysis of entrepreneurship education outcomes. *Journal of Business Venturing*, *28*(2), 211–224. https://doi.org/https://doi.org/10.1016/j.jbusvent.2012.03.002

Martin, R., & Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of Economic Geography*, *6*(4), 395–437. https://doi.org/https://doi.org/10.1093/jeg/lbl012

Masiero, L., Yang, Y., & Qiu, R. T. R. (2019). Understanding hotel location preference of customers: Comparing random utility and random regret decision rules. *Tourism Management*, *73*(April 2018), 83–93. https://doi.org/10.1016/j.tourman.2018.12.002

Massey, D. (1995). *Spatial Divisions of Labour: Social Structures and the Geography of Production*. Palgrave. Retrieved from https://www.amazon.it/Spatial-Divisions-Labour-Structures-Production/dp/0333594940

McAdam, K., Bateman, H., & Harris, E. (2005). *Dictionary of Leisure, Travel and Tourism*. A & C Black Publishers Ltd. Retrieved from https://www.amazon.it/Dictionary-Leisure-Travel-Tourism-McAdam/dp/0747572224

McCarthy, J. (2007a). What Is Artificial Intelligence?, *73*(3), 258. Retrieved from http://jmc.stanford.edu/articles/whatisai/whatisai.pdf

McCarthy, J. (2007b). What Is Artificial Intelligence?, *73*(3), 258.

Mccleary, K. W., Weaver, P. A., & Hutchinson, J. C. (1993). Hotel Selection Factors as They Relate to Business Travel Situations. *Journal of Travel Research*, *32*(2), 42–48. https://doi.org/10.1177/004728759303200206

Medlik, S. (2003). *Dictionary of Travel, Tourism and Hospitality*. Butterworth-Heinemann Title. Retrieved from https://www.routledge.com/Dictionary-of-Travel-Tourism-and-Hospitality/Medlik/p/book/9780750656504

Melo, A. J. D. V. T., Hernández-maestro, R. M., & Muñoz-gallego, P. A. (2016). Service Quality Perceptions , Online Visibility , and Business Performance in Rural Lodging Establishments. https://doi.org/10.1177/0047287516635822

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses. *Journal of Marketing Research*, *56*(4), 535–556. https://doi.org/10.1177/0022243718822827

Milkau, U. (2019). Value Creation within AI-enabled Data Platforms. *Journal of Creating Value*, *5*(1), 25–39. https://doi.org/10.1177/2394964318803244

Miloud, T., Aspelund, A., & Cabrol, M. (2012). Startup valuation by venture capitalists: An empirical study. *Venture Capital*, *14*(2–3), 151–174. https://doi.org/https://doi.org/10.1080/13691066.2012.667907

Mishra, S., & Tripathi, A. R. (2021). AI business model: an integrative business approach. *Journal of Innovation and Entrepreneurship*, *10*(1). https://doi.org/10.1186/s13731-021-00157-5

Mody, M. A., Suess, C., & Lehto, X. (2017). The accommodation experiencescape: a comparative assessment of hotels and Airbnb. *International Journal of Contemporary Hospitality Management*, *29*(9), 2377–2404. https://doi.org/10.1108/IJCHM-09-2016-0501

Montgomery, C. A., & Wernerfelt, B. (1988). Diversification , Ricardian Rents , and Tobin's q. *The RAND Journal of Economics*, *19*(4), 623–632. https://doi.org/10.2307/2555461

Murphy, J., Hofacker, C., & Gretzel, U. (2017). Dawning of the age of robots in hospitality and tourism: Challenges for teaching and research. *European Journal of Tourism Research*, *15*(July 2018), 104–111. Retrieved from https://www.cabi.org/leisuretourism/abstract/20173129512

Nambisan, S. (2016). Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship. *Entrepreneurship: Theory and Practice*, *41*(6), 1029–1055. https://doi.org/https://doi.org/10.1111/etap.12254

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly: Management Information Systems*, *41*(1), 223–238. https://doi.org/10.25300/MISQ/2017/411.03

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, *48*(8), 103773. https://doi.org/https://doi.org/10.1016/j.respol.2019.03.018

Nanda, R., & Rhodes-Kropf, M. (2013). Investment cycles and startup innovation. *Journal of Financial Economics*, *110*(2), 403–418. https://doi.org/http://dx.doi.org/10.1016/j.jfineco.2013.07.001High-technology entrepreneurship

Naughton, J. (2016). The evolution of the Internet: from military experiment to

General Purpose Technology. *Journal of Cyber Policy*, *1*(1), 5–28. https://doi.org/10.1080/23738871.2016.1157619

Nilsson, N. J. (1998). *Artificial Intelligence: A New Synthesis*. Morgan Kaufman Publishers, Inc.

Oakey, R. (2012). *High-Technology Entrepreneurship* (1st editio). London: Taylor & Francis. https://doi.org/https://doi.org/10.4324/9780203120750

Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: a new era has begun. *Small Business Economics*, *55*(3), 529–539. https://doi.org/https://doi.org/10.1007/s11187-019-00202-4

OECD Science. (2017). *Technology and Industry Scoreboard 2017* (OECD Science, Technology and Industry Scoreboard). OECD. https://doi.org/10.1787/9789264268821-en

Oskam, J., van der Rest, J. P., & Telkamp, B. (2018). What's mine is yours—but at what price? Dynamic pricing behavior as an indicator of Airbnb host professionalization. *Journal of Revenue and Pricing Management*, *17*(5), 311–328. https://doi.org/10.1057/s41272-018-00157-3

Paiva, C. J. H. de, & Vasconcelos, P. Y. (2019, January 1). The dynamic capabilities of AccorHotels in Brazil. *Journal of Hospitality and Tourism Insights*. https://doi.org/10.1108/JHTI-03-2019-0034

Panyik, E., Costa, C., & Rátz, T. (2011). Implementing integrated rural tourism: An event-based approach. *Tourism Management*, *32*(6), 1352–1363. https://doi.org/10.1016/j.tourman.2011.01.009

Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform Revolution: How Networked Markets Are Transforming the Economy and How to Make Them Work for You*. W. W. Norton.

Perez-Aranda, J., Vallespín, M., & Molinillo, S. (2019). Hotels' online reputation management: benefits perceived by managers. *International Journal of Contemporary Hospitality Management*, *31*(2), 615–632. https://doi.org/10.1108/IJCHM-07-2017-0460

Pesapane, F., Volonté, C., Codari, M., & Sardanelli, F. (2018). Artificial intelligence as a medical device in radiology: ethical and regulatory issues in Europe and the United States. *Insights into Imaging*, *9*(5), 745–753. https://doi.org/https://doi.org/10.1007/s13244-018-0645-y

Petrou, A., Pantziou, E. F., Dimara, E., & Skuras, D. (2007). Resources and activities complementarities: The role of business networks in the provision of integrated rural tourism. *Tourism Geographies*, *9*(4), 421–440. https://doi.org/10.1080/14616680701647634

Piccoli, G. (2008). A framework for evaluating the business value of customer data in hospitality. *Journal of Hospitality and Leisure Marketing*, *17*(1–2), 4–29. https://doi.org/10.1080/10507050801978331

Pikkemaat, B., & Peters, M. (2006). Towards the Measurement of Innovation—A Pilot Study in the Small and Medium Sized Hotel Industry. *Journal of Quality Assurance in Hospitality & Tourism*, *6*(3–4), 89–112. https://doi.org/10.1300/J162v06n03_06

Pine II, B. J., & Gilmore, J. H. (1998). Welcome to the Experience Economy. *Harvard Business Review*, (July-August). Retrieved from https://hbr.org/1998/07/welcome-to-the-experience-economy

Porter, M. E. (1979). How Competitive Forces Shape Strategy. *Harvard Business Review*. Retrieved from https://hbr.org/1979/03/how-competitive-forces-shape-strategy

Porter, M. E. (1981). The Contributions of Industrial Organization To Strategic Management. *The Academy OfManagement Review*, *6*(4), 609–620. https://doi.org/10.2307/257639

Postel, J. (1981a). INTERNET PROTOCOL. Retrieved December 8, 2021, from https://datatracker.ietf.org/doc/html/rfc791

Postel, J. (1981b). TRANSMISSION CONTROL PROTOCOL. Retrieved December 8, 2021, from https://datatracker.ietf.org/doc/html/rfc793

Prieto-Rodriguez, J., & Gonzalez-Díaz, M. (2008). Is there an economic rent for island hotels? *Tourism Economics*, *14*(1), 131–154. https://doi.org/10.5367/000000008783554839

Pröbstl-Haider, U. (2010). Strategies for tourism development in peripheral areas in the alpine area. *WIT Transactions on Ecology and the Environment*, *139*, 3–11. https://doi.org/10.2495/ST100011

Pröbstl-Haider, U., Melzer, V., & Jiricka, A. (2014). Rural tourism opportunities: Strategies and requirements for destination leadership in peripheral areas. *Tourism Review*, *69*(3), 216–228. https://doi.org/10.1108/TR-06-2013-0038

Purcell, M. (2014). Possible worlds: Henri lefebvre and the right to the city. *Journal of Urban Affairs*, *36*(1), 141–154. https://doi.org/10.1111/juaf.12034

Qian, G., & Li, L. (2003). Profitability of small- and medium-sized enterprises in high-tech industries: The case of the biotechnology industry. *Strategic Management Journal*, *24*(9), 881–887. https://doi.org/10.1002/smj.344

Quattrone, G., Greatorex, A., Quercia, D., Capra, L., & Musolesi, M. (2018). Analyzing and predicting the spatial penetration of Airbnb in U.S. cities. *EPJ Data Science*, *7*(1). https://doi.org/10.1140/epjds/s13688-018-0156-6

Raguseo, E., & Vitari, C. (2017). The Effect of Brand on the Impact of e-WOM on Hotels' Financial Performance. *International Journal of Electronic Commerce*, *21*(2), 249–269. https://doi.org/10.1080/10864415.2016.1234287

Ratzinger, D., Amess, K., Greenman, A., & Mosey, S. (2018). The impact of digital start-up founders' higher education on reaching equity investment milestones. *The Journal of Technology Transfer*, *43*(3), 760–778. https://doi.org/https://doi.org/10.1007/s10961-017-9627-3

Rayna, T., Striukova, L., & Darlington, J. (2015). Co-creation and user innovation: The role of online 3D printing platforms. *Journal of Engineering and Technology Management - JET-M*, *37*, 90–102. https://doi.org/10.1016/j.jengtecman.2015.07.002

Ritchie, J. R. B., & Crouch, G. I. (2003). *The competitive destination: a sustainable tourism perspective*. Wallingford, United Kingdom: CABI Publishing. https://doi.org/http://dx.doi.org/10.1079/9780851996646.0000

Roma, P., Panniello, U., & Lo Nigro, G. (2019). Sharing economy and incumbents' pricing strategy: The impact of Airbnb on the hospitality industry. *International Journal of Production Economics*, *214*, 17–29. https://doi.org/10.1016/J.IJPE.2019.03.023

Romero, I., & Tejada, P. (2011). A multi-level approach to the study of production chains in the tourism sector. *Tourism Management*, *32*(2), 297–306. https://doi.org/http://dx.doi.org/10.1016/j.tourman.2010.02.006

Ruef, M., Aldrihc, H. E., & Carter, N. M. (2004). The Structure of Founding Teams: Homophily, Strong Ties, and Isolation among U.S. Entrepreneurs. *American Sociological Review*, *69*(2), 297. https://doi.org/10.1177/000312240406900208

Russell, S., & Norvig, P. (2020). *Artificial Intelligence: A Modern Approach*. Retrieved from https://www.amazon.it/Artificial-Intelligence-Approach-Stuart-Russell/dp/0136042597

Russo, A. P. (2002). The "vicious circle" of tourism development in heritage cities.

Annals of Tourism Research, *29*(1), 165–182. https://doi.org/10.1016/S0160-7383(01)00029-9

Sainaghi, R. (2011). RevPAR determinants of individual hotels: Evidences from Milan. *International Journal of Contemporary Hospitality Management*, *23*(3), 297–311. https://doi.org/10.1108/09596111111122497

Sainaghi, R., & Canali, S. (2011). Exploring the effects of destination's positioning on hotels' performance: The Milan case. *TOURISMOS: AN INTERNATIONAL MULTIDISCIPLINARY JOURNAL OF TOURISM*, *6*(2), 121–138.

Samala, N., Katkam, B. S., Bellamkonda, R. S., & Rodriguez, R. V. (2020). Impact of AI and robotics in the tourism sector: a critical insight. *Journal of Tourism Futures*. https://doi.org/https://doi.org/10.1108/JTF-07-2019-0065

Samara, D., Magnisalis, I., & Peristeras, V. (2020). Artificial intelligence and big data in tourism: a systematic literature review. *Journal of Hospitality and Tourism Technology*, *11*(2), 343–367. https://doi.org/https://doi.org/10.1108/JHTT-12-2018-0118

Samoili, S., López Cobo, M., Gómez, E., De Prato, G., Martínez-Plumed, F., & Delipetrev, B. (2020). *AI Watch - Defining Artificial Intelligence. Towards an operational definition and taxonomy of artificial intelligence*. *Joint Research Centre (European Commission)*. https://doi.org/https://doi.org/10.2760/382730Regional Advantage: Culture and Competition in Silicon Valley and Route 128

Saxenian, A. (1996). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128, With a New Preface by the Author*. Harvard University Press. https://doi.org/https://doi.org/10.2307/j.ctvjnrsqh

Schilling, M. A. (2002). Technology success and failure in winner-take-all markets: The impact of learning orientation, timing, and network externalities. *Academy of Management Journal*, *45*(2), 387–398. https://doi.org/10.2307/3069353

Schmidt, G. M., & Druehl, C. T. (2008). When is a disruptive innovation disruptive? *Journal of Product Innovation Management*, *25*(4), 347–369. https://doi.org/10.1111/j.1540-5885.2008.00306.x

Schoenmueller, V., Netzer, O., & Stahl, F. (2018). The Extreme Distribution of Online Reviews: Prevalence, Drivers and Implications. *SSRN Electronic Journal*, (February), 1–62. https://doi.org/10.2139/ssrn.3100217

Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and Tourism Online

Reviews: Recent Trends and Future Directions. *Journal of Travel and Tourism Marketing*, *32*(5), 608–621. https://doi.org/10.1080/10548408.2014.933154

Schultz, T. W. (1961). Investment in human capital. *The American Economic Review*, *51*(1), 1–17. Retrieved from https://www.ssc.wisc.edu/~walker/wp/wp-content/uploads/2012/04/schultz61.pdf

Sequera, J., & Nofre, J. (2018). Shaken, not stirred. *City*, *22*(5–6), 843–855. https://doi.org/10.1080/13604813.2018.1548819

Sharpley, R. (2006). *Travel and Tourism*. SAGE Publications Inc. Retrieved from https://books.google.it/books?hl=it&lr=&id=9TcCUXzRYfcC&oi=fnd&pg=PP2&dq=Travel+and+Tourism+Sharpley&ots=Hble5ovsQU&sig=28M7DyoyaBQ6WXabzwoLbztSbFQ#v=onepage&q=Travel and Tourism Sharpley&f=false

Shoval, N. (2006). The geography of hotels in cities: An empirical validation of a forgotten model. *Tourism Geographies*, *8*(1), 56–75. https://doi.org/10.1080/14616680500392499

Smithson, S., Devece, C. A., & Lapiedra, R. (2011). Online visibility as a source of competitive advantage for small- and medium-sized tourism accommodation enterprises, *2069*. https://doi.org/10.1080/02642069.2010.485640

Solvoll, S., Alsos, G. A., & Bulanova, O. (2015). Tourism Entrepreneurship – Review and Future Directions. *Scandinavian Journal of Hospitality and Tourism*, *15*(January 2018), 120–137. https://doi.org/https://doi.org/10.1080/15022250.2015.1065592

Srinivasan, A., & Venkatraman, N. (2018). Entrepreneurship in digital platforms: A network-centric view. *Strategic Entrepreneurship Journal*, *12*(1), 54–71. https://doi.org/10.1111/sej.1272

Stinchcombe, A. L. (1965). Social Structure and Organizations. In *Handbook of Organizations* (pp. 142–193).

Strømmen-Bakhtiar, A., Vinogradov, E., Kvarum, M. K., & Antonsen, K. R. (2020). Airbnb Contribution to Rural Development: The Case of a Remote Norwegian Municipality. *International Journal of Innovation in the Digital Economy*, *11*(2), 31–46. https://doi.org/10.4018/ijide.2020040103

Sun, L., Wang, S., Liu, S., Yao, L., Luo, W., & Shukla, A. (2018). A completive research on the feasibility and adaptation of shared transportation in mega-cities – A case study in Beijing. *Applied Energy*, *230*(May), 1014–1033.

https://doi.org/10.1016/j.apenergy.2018.09.080

Swarbrooke, J., & Horner, S. (2001). *Business Travel and Tourism*. Routledge. Retrieved from http://repository.mut.ac.ke:8080/xmlui/bitstream/handle/123456789/39/Business Travel and Tourism %282001%29.pdf?sequence=1&isAllowed=y

Taddy, M. (2018). *The Technological Elements of Artificial Intelligence* (NBER Working Paper Series No. 24301). https://doi.org/10.3386/w24301

Talwar, R., & Koury, A. (2017). Artificial intelligence – the next frontier in IT security? *Network Security*, *2017*(4), 14–17. https://doi.org/https://doi.org/10.1016/S1353-4858(17)30039-9

Teece, D. J. (2007). EXPLICATING DYNAMIC CAPABILITIES: THE NATURE AND MICROFOUNDATIONS OF (SUSTAINABLE) ENTERPRISE PERFORMANCE. *Strategic Management Journal*, *28*, 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J. (2014). THE FOUNDATIONS OF ENTERPRISE PERFORMANCE:DYNAMIC AND ORDINARY CAPABILITIES IN AN(ECONOMIC) THEORY OF FIRMS. *The Academy of Management Perspectives*, *28*(4), 328–352. https://doi.org/10.5465/amp.2013.0116

Teodoro, A., Dinis, I., Simões, O., & Gomes, G. (2017). Success factors for small rural tourism units : an exploratory study in the Portuguese region of Serra da Estrela Success factors for small rural tourism units : an exploratory study in the Portuguese region of Serra da Estrela, (July 2020).

Terhorst, P., & Erkuş-Özturk, H. (2011). Scaling, territoriality, and networks of a tourism place. *Anatolia*, *22*(2), 168–183. https://doi.org/10.1080/13032917.2011.597932

Teubner, T., Hawlitschek, F., & Dann, D. (2017). Price Determinants on Airbnb: How Reputation Pays Off in the Sharing Economy. *Journal of Self-Governance and Management Economics*, *5*(4), 53. https://doi.org/10.22381/jsme5420173

Thébaud, S. (2015). Business as Plan B: Institutional Foundations of Gender Inequality in Entrepreneurship across 24 Industrialized Countries. *Administrative Science Quarterly*, *60*(4), 671–711. https://doi.org/https://doi.org/10.1177/0001839215591627

Thébaud, S., & Charles, M. (2018). Segregation, stereotypes, and STEM. *Social Sciences*, *7*(7), 1–18. https://doi.org/https://doi.org/10.3390/socsci7070111

Thirumalesh Madanaguli, A., Kaur, P., Bresciani, S., & Dhir, A. (2021). Entrepreneurship in rural hospitality and tourism. A systematic literature review of past achievements and future promises. *International Journal of Contemporary Hospitality Management*, *33*(8), 2521–2558. https://doi.org/10.1108/IJCHM-09-2020-1121

TOPHOTELNEWS. (2017). Airbnb now has more room listings than the top 5 hotel brands combined. Retrieved from https://tophotel.news/airbnb-now-has-more-room-listings-than-the-top-5-hotel-brands-combined/

Tractica. (2019). Forecast growth of the artificial intelligence (AI) software market worldwide from 2019 to 2025. Retrieved February 7, 2021, from https://www-statista-com/statistics/607960/worldwide-artificial-intelligence-market-growth/

Tsaih, R. H., & Hsu, C. C. (2018). Artificial intelligence in smart tourism: A conceptual framework. *Proceedings of the International Conference on Electronic Business (ICEB)*, *2018-Decem*, 124–133.

TUI. (2018). Market size of the global hotel industry from 2014 to 2018 (in billion U.S. dollars) [Graph]. Retrieved from https://www.statista.com/statistics/247264/total-revenue-of-the-global-hotel-industry/

Tung, V. W. S., & Au, N. (2018). Exploring customer experiences with robotics in hospitality. *International Journal of Contemporary Hospitality Management*, *30*(7), 2680–2697. https://doi.org/https://doi.org/10.1108/IJCHM-06-2017-0322

Tung, V. W. S., & Law, R. (2017). The potential for tourism and hospitality experience research in human-robot interactions. *International Journal of Contemporary Hospitality Management*, *29*(10), 2498–2513. https://doi.org/https://doi.org/10.1108/IJCHM-09-2016-0520

Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Annals of Tourism Research*, *81*(December 2018), 102883. https://doi.org/https://doi.org/10.1016/j.annals.2020.102883

Tussyadiah, I. P., & Park, S. (2018). Consumer Evaluation of Hotel Service Robots. *Information and Communication Technologies in Tourism 2018*, *2018*, 308–320. https://doi.org/https://doi.org/10.1007/978-3-319-72923-7_24

Tussyadiah, I. P., & Pesonen, J. (2016). Impacts of Peer-to-Peer Accommodation Use on Travel Patterns. *Journal of Travel Research*, *55*(8), 1022–1040.

https://doi.org/10.1177/0047287515608505

Valsamidis, S. I., Maditinos, D., & Mandilas, A. (2020). Innovative Business Models in Tourism Industry. In *INNODOCT 2019*. https://doi.org/10.4995/inn2019.2019.10146

Van Der Sluis, J., Van Praag, M., & Vijverberg, W. (2008). Education and entrepreneurship selection and performance: A review of the empirical literature. *Journal of Economic Surveys*, *22*(5), 795–841. https://doi.org/https://doi.org/10.1111/j.1467-6419.2008.00550.x

von Briel, F., Davidsson, P., & Recker, J. (2018). Digital technologies as external enablers of new venture creation in the it hardware sector. *Entrepreneurship: Theory and Practice*, *42*(1), 47–69. https://doi.org/https://doi.org/10.1177/1042258717732779

von Briel, F., Recker, J., & Davidsson, P. (2018). Not all digital venture ideas are created equal: Implications for venture creation processes. *Journal of Strategic Information Systems*, *27*(4), 278–295. https://doi.org/10.1016/j.jsis.2018.06.002

Wachsmuth, D., & Weisler, A. (2018). Airbnb and the rent gap: Gentrification through the sharing economy. *Environment and Planning A*, *50*(6), 1147–1170. https://doi.org/10.1177/0308518X18778038

Walsh, S. T. (2004). Roadmapping a disruptive technology: A case study The emerging microsystems and top-down nanosystems industry. *Technological Forecasting and Social Change*, *71*(1–2), 161–185. https://doi.org/10.1016/j.techfore.2003.10.003

Wang, W., & Siau, K. (2018). Artificial Intelligence: A Study on Governance, Policies, and Regulations. In *Proceedings of the Thirteenth Midwest Association for Information Systems Conference* (p. 40). Saint Louis, Missouri. Retrieved from http://aisel.aisnet.org/mwais2018/40

Weiermair, K. (2006). Product improvement or innovation: what is the key to success in tourism? In *Innovation and Growth in Tourism*. Paris: OECD Publishing. https://doi.org/https://doi.org/10.1787/9789264025028-en

Weiermair, K. (2008). Prospects for Innovation in Tourism. *Journal of Quality Assurance in Hospitality & Tourism*, *6*(3), 59–72. https://doi.org/10.1300/J162v06n03

Weiermair, K., & Kronenberg, C. (2004). Stuck in the middle: strategies for improving the market position of SMEs in tourism. *The Poznań University of*

Economics Review, *4*(1), 103–112.

Weiner, N., & Mahoney, T. A. (1981). A Model of Corporate Performance as a Function of Environmental, Organizational, and Leadership Influences. *Academy of Management Journal*, *24*(3), 453–470. https://doi.org/10.5465/255568

Welter, F., Baker, T., & Wirsching, K. (2019). Three waves and counting: the rising tide of contextualization in entrepreneurship research. *Small Business Economics*, *52*(2), 319–330. https://doi.org/https://doi.org/10.1007/s11187-018-0094-5

Wensveen, J. G., & Leick, R. (2009). The long-haul low-cost carrier: A unique business model. *Journal of Air Transport Management*, *15*(3), 127–133. https://doi.org/10.1016/j.jairtraman.2008.11.012

Wernerfelt, B. (1984). A Resource-Based View of the Firm. *Strategic Management Journal*, *5*(2), 171–180. https://doi.org/https://doi.org/10.1002/smj.4250050207

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, *24*(10 SPEC ISS.), 991–995. https://doi.org/10.1002/smj.318

Wolf, M. J. (1999). *The Entertainment Economy: How Mega-media Forces are Transforming Our Lives*. Times Books. Retrieved from https://books.google.it/books?id=qFgUX17jpTQC

World Economic Forum. (2017). *Digital Transformation Initiative Aviation, Travel and Tourism Industry*. Retrieved from http://reports.weforum.org/digital-transformation/

World Tourism Organization. (2019). *International Tourism Highlights*. Madrid. https://doi.org/https://doi.org/10.18111/9789284421152

WTTC. (2018). Direct and total contribution of travel and tourism to GDP from 2006 to 2017 (in billion U.S. dollars) [Graph]. Retrieved from https://www.statista.com/statistics/233223/travel-and-tourism--total-economic-contribution-worldwide/

Xie, K. L., & Kwok, L. (2017). The effects of Airbnb's price positioning on hotel performance. *International Journal of Hospitality Management*, *67*(December 2016), 174–184. https://doi.org/10.1016/j.ijhm.2017.08.011

Xie, K., Wu, Y., Xiao, J., & Hu, Q. (2016). Value co-creation between firms and customers: The role of big data-based cooperative assets. *Information and*

Management, *53*(8), 1034–1048. https://doi.org/https://doi.org/10.1016/j.im.2016.06.003

Yang, Y., Luo, H., & Law, R. (2014). Theoretical, empirical, and operational models in hotel location research. *International Journal of Hospitality Management*, *36*, 209–220. https://doi.org/10.1016/j.ijhm.2013.09.004

Yokeno, N. (1968). La Localisation de l’industrie touristique : application de l’analyse de Thunen-Weber. *Cahiers Du Tourisme*, *C*(9).

Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for Innovation in the Digitized World. *Organization Science*, *23*(5), 1398–1408. https://doi.org/10.1287/orsc.1120.0771

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322

Yu, C.-E. (2020). Humanlike robots as employees in the hotel industry: Thematic content analysis of online reviews. *Journal of Hospitality Marketing and Management*, *29*(1), 22–38. https://doi.org/https://doi.org/10.1080/19368623.2019.1592733

Zaheer, H., Breyer, Y., & Dumay, J. (2019). Digital entrepreneurship: An interdisciplinary structured literature review and research agenda. *Technological Forecasting and Social Change*, *148*(June 2018), 119735. https://doi.org/https://doi.org/10.1016/j.techfore.2019.119735

Zeng, J., Mahdi Tavalaei, M., & Khan, Z. (2021). Sharing economy platform firms and their resource orchestration approaches. *Journal of Business Research*, *136*, 451–465. https://doi.org/10.1016/j.jbusres.2021.07.054

Zervas, G., Proserpio, D., & Byers, J. (2017). The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *Journal of Marketing Research*, *54*(5). https://doi.org/https://doi.org/10.1509/jmr.15.0204

Zhang, Zhihua, & Chen, R. J. C. (2019). Assessing Airbnb logistics in cities: Geographic information system and convenience theory. *Sustainability (Switzerland)*, *11*(9), 1–11. https://doi.org/10.3390/su11092462

Zhang, Ziqiong, Ye, Q., & Law, R. (2011). Determinants of hotel room price: An exploration of travelers’ hierarchy of accommodation needs. *International Journal of Contemporary Hospitality Management*, *23*(7), 972–981. https://doi.org/10.1108/09596111111167551

Chapter 8

Appendix

Appendix 1

Authors	**Geography**	**Title**	**Hypotheses**	**Independent variables**	**Moderation variables**	**Dependent variable**	**Results**	**Airbnb impact on hotel (+/-)**
Zervas G., Proserpio D., Byers J.W. 2016	Main cities in Texas (Houston, San Antonio, Dallas, Austin,	The rise of the sharing economy: Estimating the	Airbnb has a measurable and quantifiable impact on hotel revenues in the areas of interest	Airbnb supply		Hotel revenues	A 10% increase in Airbnb listings associated with a 0.35% decrease in	Direct negative

	Fort Worth, El Paso, Arlington, Corpus Christi, Plano and Laredo)	impact of Airbnb on the hotel industry					monthly hotel room revenues	
			Airbnb has a measurable and quantifiable impact on the Occupation rate of a hotel in the areas of interest	Airbnb supply		Hotel OCC	A 10% increase in Airbnb supply generates a near-zero decrease in the occupancy rate of about 0.0005%	Direct negative
			Airbnb has a measurable and quantifiable impact on the ADR of a hotel in the areas of interest	Airbnb supply		Hotel ADR	A 10% increase in Airbnb supply is associated with a price decrease of 0.19%	Direct negative
			Airbnb has a measurable and quantifiable impact on hotel revenues in the areas of interest, but high-end hotels suffer less	Airbnb supply	Hotel type	Hotel revenues	The negative impact of Airbnb increases as the price tiers decrease; an insignificant effect observed for the Upscale and Luxury segment	Moderating negative
			Airbnb has a measurable and quantifiable impact on hotel revenues in the areas of interest, but business hotels suffer less	Airbnb supply	Business hotel	Hotel revenues	A lack of meeting spaces is negative and statistically significant	Moderating negative
			Airbnb has a measurable and quantifiable impact on hotel revenues in the areas of interest, but hotels belonging to a chain suffer less	Airbnb supply	Chain hotel	Hotel revenues	Hotels of both operation structures are affected. However Airbnb has a slightly larger	Moderating negative

								impact on independent hotels	
	Austin & Dallas, Texas		Airbnb reduces the pricing power of hotels (dynamic pricing during large events)	Airbnb supply		Hotel peak pricing power during large events	The pricing power of hotels has declined significantly as Airbnb popularity has grown, despite the fact that SXSW attendance has continued to grow steadily over time	Direct negative
Xie K.L., Kwok L. 2017	Austin, Texas	The effects of Airbnb's price positioning on the performance of hotels	The supply of Airbnb listings negatively impacts the performance of local hotels	Same Postal code listing supply		Revpar	The supply of the accommodation alternatives of Airbnb listings in the same Postal code area significantly impacts the revpar of hotels	Direct negative
			Price difference between a hotel and Airbnb listings in the vicinity has a significant impact on the performance of the hotel	Price difference between a hotel and Airbnb listings nearby		Revpar	The revpar of hotels increases along with the price difference between hotels and Airbnb with the same Postal code	Direct negative
			Price dispersion among Airbnb listings in the vicinity has a significant impact on the performance of a hotel	Price dispersion among Airbnb		Revpar	The revpar of hotels increases along with the dispersion of prices for Airbnb	Direct negative

				listings nearby			with the same Postal code	
			The price difference between a hotel and Airbnb listings in the vicinity moderates the relationship between the local Airbnb supply and the performance of a hotel, where a larger price gap will lower the negative impact of the local Airbnb supply on the performance of a hotel	Same Postal code listing supply	Price difference between a hotel and Airbnb listings nearby	Revpar	The moderation of the price difference on the impact of the Airbnb supply was found to be significant	Moderating negative
			Price dispersion among Airbnb listings in the vicinity moderates the relationship between the local Airbnb supply and the performance of a hotel, where a larger price dispersion will lower the negative impact of the local Airbnb supply on the performance of a hotel	Same Postal code listing supply	Price dispersion among Airbnb listings nearby	Revpar	The moderation of the price difference on the impact of the Airbnb supply was found to be significant	Moderating negative
			The hotel class moderates the relationship between the local Airbnb supply and the performance of a hotel, where hotels in a lower-tier class are impacted more negatively by the local Airbnb supply than those in a higher-tier class	Same Postal code listing supply	Hotel class	Revpar	Not supported	Not significant
			The online ratings of a hotel moderate the relationship between the local Airbnb supply and the performance of the hotel, where hotels with lower review ratings are impacted more negatively by the local Airbnb supply than those with higher review ratings	Same Postal code listing supply	Online ratings	Revpar	Not supported	Not significant
Blal I., Singal M., Templin J. 2018	San Francisco, California	Airbnb's effect on hotel sales growth	The total Airbnb supply is negatively associated with the sales pattern performance of a hotel (revpar)	Total Airbnb supply		Hotel revpar	Non-significant effect on revpar	Not significant
			The average prices of Airbnb rentals are positively associated with the sales pattern performance of hotels	Average Airbnb price		Hotel revpar	The Airbnb property prices showed a positive effect on the hotel revpar: the	Direct positive

							higher the price of the rentals posted on the platform, the higher the revpar of hotels	
			The average satisfaction of Airbnb users is negatively associated with the sales pattern performance of hotels	Average score of Airbnb listings		Hotel revpar	Negative relationship between hotel revpar and the average satisfaction rate of Airbnb guests	Direct negative
			The effects of Airbnb on the sales pattern performance of hotels varies across different hotel segments	Average Airbnb price	Hotel star category	Hotel revpar	5 stars: increase in revpar of $0.651 for each increase in dollars in the average price 4 stars: lower effect ($0.459) for each increase in dollars in the average price	Moderating positive
Dogru T., Mody M., Suess C. 2019	Boston, Massachusetts & Chicago, Illinois	Adding evidence to the debate: Quantifying Airbnb's disruptive impact on ten key hotel markets	The Airbnb supply negatively impacts hotel room revenues (revpar), i.e., the revpar of hotels decreases for an increased Airbnb supply.	Total cumulative active Airbnb listings for the last 12 months		Revpar	A 1% increase in Airbnb supply decreases the revpar of a hotel by 0.02%	Direct negative
			The Airbnb supply negatively impacts the average daily rates (ADR) of a hotel, i.e., the ADR of a hotel decreases for an increased Airbnb supply			ADR	A 1% increase in Airbnb supply (both total cumulative and active supply) decreases ADR by 0.02%	Direct negative

			The Airbnb supply negatively impacts the occupancies (OCC) of hotels, i.e., the OCC of hotels decreases for an increased Airbnb supply			Occupancy rate	A 1% increase in Airbnb supply decreases the OCC of hotels by between 0.001% and 0.004%	Direct negative
Ginindza, Tichaawa 2017	Mbabane, Ezulwini, Matsapha and Manzini, Swaziland	The impact of sharing accommodation on the occupancy rate of hotels in the kingdom of Swaziland	The sharing accommodation platform has a statistically significant negative impact on the HOR	Airbnb occupancy rate		Hotel occupancy rate	The Airbnb occupancy rate has a statistically significant positive relationship with the HOR	Direct positive
Aznar J.P., Sayeras J.M., Rocafort A., Galiana J. 2017	Barcelona, Spain	The irruption of Airbnb and its effects on hotel profitability: An analysis of Barcelona's hotel sector	Profitability is negatively affected when there is a major presence of apartments nearby	Airbnb supply in a radius of 1 km from a hotel		ROE	Positive correlation between the presence of Airbnb apartments and return on equity	Direct positive
			Profitability is positively affected by the size of a hotel	Hotel size		ROE	Positive but not significant	Not significant
			Profitability is positively affected by the star rating of a hotel	Hotel star category		ROE	Not supported	Not significant
Choi K.-H., Jung J., Ryu S., Kim S.-D., Yoon S.-M. 2015	Seoul, Busan, and Jeju, South Korea	The relationship between Airbnb and a hotel's revenues: The case of Korea	Airbnb's listings have a negative impact on the revenues of a hotel in Korea	Airbnb listing number		Hotel revenues	Not supported	Not significant

Roma P., Panniello U., Lo Nigro G. 2019	The main touristic cities in Italy (Bologna, Florence, Genoa, Milan, Naples, Padua, Palermo, Pisa, Ravenna, Rome, Turin, Venice and Verona)	Sharing economy and incumbents' pricing strategy: The impact of Airbnb on the hospitality industry	Low/medium-end incumbents (i.e., 1–3 star hotels) set lower average prices and the best deals in certain geographical areas (i.e., cities), where the players' penetration of the sharing economy is higher than in areas where the players' penetration of the sharing economy is less pronounced, ceteris paribus. However, these lower prices are only offered for weekend accommodation, and not for weekday accommodation.	Players' (Airbnb) penetration of the sharing economy	Weekend vs weekdays	The average prices and Minimum Price of 1-3 star hotels	Higher penetration of Airbnb, related to a price reduction during weekends in all the cities Airbnb penetration does not affect prices to any great extent on weekdays	Moderating negative
			High-end incumbents (i.e., 4–5 star hotels) set higher best deals and average prices in certain geographical areas (i.e., cities), where the players' penetration of the sharing economy is higher than in areas where the players' penetration of the sharing economy is less pronounced, ceteris paribus. Moreover, these higher prices are offered irrespective of the period of the accommodation search (weekends or weekdays)	Players' (Airbnb) penetration of the sharing economy	Weekend vs weekdays	The average prices and Minimum Prices of 4-5 star hotels	Higher penetration of Airbnb, related to a price increase, irrespective of the day of the week	Not significant

Appendix 1: Literature review on Airbnb impact on hotels

Appendix 2

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Travel inspiration	1.000																				
2	Booking and preparation	-0.004	1.000																			
3	Transport services	-0.385 *	-0.301*	1.000																		
4	Destination services	-0.138	-0.309 *	-0.203	1.000																	
5	Post-trip	0.234 *	0.017	-0.233 *	-0.071	1.000																
6	Reasoning	0.251 *	0.007	-0.097	-0.112	0.085	1.000															
7	Planning	NA	NA	NA	NA	NA	NA	NA														
8	Learning	0.092	-0.035	0.216 *	-0.099	-0.100	0.046	NA	1.000													
9	Communication	0.090	0.192	-0.330 *	-0.241 *	0.234 *	-0.134	NA	-0.180	1.000												
10	Perception	-0.119	-0.222 *	0.144	0.285 *	-0.187	-0.078	NA	-0.014	-0.182	1.000											
11	Integration and Interaction	-0.077	-0.071	0.199	-0.064	-0.046	-0.019	NA	-0.057	-0.077	-0.044	1.000										
12	Services	0.180	-0.018	-0.016	0.043	-0.147	-0.086	NA	0.007	-0.418 *	-0.30 *	-0.120	1.000									
13	AI Ethics and Philosophy	-0.199	-0.178	0.131	0.302 *	-0.163	0.121	NA	-0.121	-0.269 *	0.217 *	-0.039	0.053	1.000								
14	Total Funding Amount	0.368 *	0.207 *	-0.167	0.064	0.469 *	0.123	NA	0.232 *	-0.030	-0.225 *	0.093	0.097	0.133	1.000							
15	Number of Founders	0.115	0.036	-0.116	-0.134	0.005	-0.125	NA	-0.053	0.167	0.041	0.220 *	-0.011	0.047	0.274 *	1.000						
16	Team percentage female	-0.029	-0.192	0.011	0.105	0.039	-0.062	NA	0.209 *	0.026	0.050	-0.035	-0.158	-0.071	-0.182	0.005	1.000					

17	Team percentage STEM	-0.069	-0.152	-0.040	0.046	0.048	-0.131	NA	0.048	0.039	0.198	0.055	-0.120	-0.001	0.023	0.033	0.105	1.000				
18	Team percentage PhD	-0.133	-0.185	0.071	0.206*	-0.056	-0.079	NA	0.131	-0.210*	0.261*	0.132	-0.155	0.087	-0.109	-0.124	0.207*	0.351*	1.000			
19	Team percentage MBA	-0.188	0.146	0.049	-0.104	-0.085	-0.058	NA	0.016	0.121	-0.051	-0.033	-0.002	0.005	0.094	-0.037	-0.004	0.018	-0.041	1.000		
20	Team percentage company experience	-0.024	-0.019	0.051	-0.045	-0.047	0.097	NA	0.202	-0.008	-0.098	0.036	-0.009	-0.051	0.293*	-0.236*	0.125	0.378*	0.243*	0.267*	1.000	
21	Team percentage start-up experience	-0.156	0.197	-0.156	-0.115	-0.113	-0.094	NA	-0.240*	0.114	0.028	0.095	-0.083	0.018	0.028	-0.092	-0.156	0.113	-0.004	0.128	0.383*	1.000

Note: * p-value < 0.05; “NA” stands for “not available”.

Appendix 2: Correlation matrix

Appendix 3

Looking for specific keywords in the text, we understood the phase(s) in which the start-ups operate. For example, a start-up selling a service allowing customers to personalize the hotel rooms would use the words "hotel" and "room" on their website; since both these words belong to the booking & preparation phase, the algorithm will assign the start-up to this phase of the supply chain. Since any start-up can be assigned to more than one phase, all of them have been analyzed by the authors to ensure correct classification. We also used NVivo to expand the list of keywords used. We used the list of keywords obtained from four authoritative books on the tourism industry, but, this time, we kept all the keywords that could be possibly related to the industry and placed them in the phase of the supply chain they belong to. The extended list of keywords is available below. We used such a list as input to a Python script that checked the presence of each keyword in each website and assigned each start-up to one or more phases. This process has been verified by the authors to ensure its reliability.

Appendix 3: Start-up classification procedure

Appendix 4

	SUPPLY CHAIN PHASES				
	Inspiration	**Booking and preparation**	**Travel**	**Destination**	**Post-trip**
Supply chain phases based on scientific articles	meta search	Ota	bus	hotel operator	social media
		travel agency	trains	vacation rental	review
		travel planning	airlines	tour	
		travel development	airport	hotel	
		trip organizer	station	car rental	
		Taxi	cruise lines	taxi	
			boat	bus	
			car rental	club	
				restaurant	
				event	
NVivo keywords integration	ranking	Hotel	journey	food	referr
	marketing	Sale	travel	nutrient	post
	country	Room	trip	catering	blog
	nation	Suite	airway	home	comment
	state	Confirmation	international	visit	feedback
	town	Plan	passenger	holidaymaker	satisfaction
	incentive	Route	flight	room	
	bonus	Transport	road	suite	
	cost	Prepare	check-in	party	
	price	Program	transport	check-in	
	holiday	Agent	ticket	transport	
	advertise	Assistant	ship	hospitality	
	Adv	Payment	embark	incoming	
	attraction	Ticket	railway	assistant	
	referr	Budget	luggage	service	
	budget	Baggage	baggage	drink	
		Luggage		beverage	
		Insurance		destination	
		Available		experience	
				house	
				lodg	
				entertainment	

Appendix 4: Supply chain phases and keywords (output of NVivo software)

Appendix 5

AI technological domains / **Supply chain phases**	*Reasoning*	*Planning*	*Learning*	*Communication*	*Perception*	*Integration and Interaction*	*Services*	*AI Ethics and Philosophy*	**Total**
Travel inspiration	3 (1)	-	9 (4)	13 (6)	3 (1)	-	22 (9)	1 (0)	51 (21)
Booking and Preparation	1 (1)	-	6 (1)	14 (6)	1 (0)	-	16 (9)	1 (1)	39 (18)
Transport services	-	-	8 (5)	1 (0)	5 (2)	1 (1)	11 (4)	4 (1)	30 (13)
Destination services	-	-	4 (2)	4 (2)	8 (3)	-	15 (6)	7 (2)	38 (15)
Post-trip	1 (1)	-	2 (2)	9 (5)	-	-	6 (2)	-	18 (10)
Total	5 (3)	-	29 (14)	41 (19)	17 (6)	1 (1)	70 (30)	13 (4)	176 (77)

Note: every cell contains the number of start-ups in each crossing between supply chain phases and AI technological domains of application, and in parenthesis, it is specified the number of start-up that received some funds.

Appendix 5: Number of start-ups by supply chain phase and AI technological domains

Appendix 6

Domain of application the start-up belongs to (single domain)	Frequency	Percentage
Only in Services	25	27.17%
Only in Communication	20	21.74%
Only in Learning	4	4.35%
Only in Reasoning	2	2.17%
Only in Computer vision	2	2.17%
Only in Perception	1	1.09%
Only in Connected and Automated vehicles	1	1.09%
Sub-total	55	59.78%
Domains of application the start-up belongs to (multiple domains)		
Learning; Services	9	9.78%
Services; AI Ethics	6	6.52%
Communication; Services	6	6.52%
Computer vision; AI Ethics	4	4.35%
Learning; Computer vision	3	3.26%
Learning; Communication	2	2.17%
Learning; Communication; Services	2	2.17%
Perception; Communication; Services	1	1.09%
Computer vision; Services	1	1.09%
Communication; Computer vision	1	1.09%
Audio processing; Services	1	1.09%
Reasoning; Learning; Services; AI Ethics	1	1.09%
Sub-total	37	40.22%

Appendix 6: Start-up domains of application co-occurrences

Appendix 7

Phase of the supply chain where the start-up operates (single phase)	Frequency	Percentage
Only in Transport services	17	18.48%
Only in Destination services	17	18.48%
Only in Booking and Preparation	17	18.48%
Only in Travel inspiration	14	15.22%
Only in Post-trip	5	5.43%
Sub-total	70	76.09%
Phases of the supply chain where the start-up operates (multiple phases)		
Travel inspiration; Booking and Preparation	6	6.52%
Travel inspiration; Post-trip	4	4.35%
Travel inspiration; Destination services	3	3.26%
Travel inspiration; Booking and Preparation; Post-trip	2	2.17%
Transport services; Destination services	2	2.17%
Travel inspiration; Booking and Preparation; Destination services; Post-trip	2	2.17%
Travel inspiration; Destination services; Post-trip	1	1.09%
Booking and Preparation; Post-trip	1	1.09%
Booking and Preparation; Transport services	1	1.09%
Sub-total	22	23.91%

Appendix 7: Start-up supply chain phases co-occurrences