The 4th Industrial (R)evolution: the role of service robots in online discourse

Doctor of Philosophy in Management

Henley Business School, the Department of Leadership, Organisations and Behaviour

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November 2020

Declaration of original authorship

I confirm that this thesis I present for the examination for the PhD degree at Henley Business School, University of Reading is my own work, other than where I have clearly indicated that it is work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it). The use of all material from other sources has been properly and fully acknowledged.

Author Signature: *Matteo Borghi*

Statement of Conjoint work

I confirm that Paper 1 (**Chapter 2** of the thesis) was co-authored with my 1st supervisor Professor Marcello M. Mariani. My overall contribution as a lead author is 60%**.** This includes the literature review, data collection, data analysis, and interpretation and drafting of the article. Professor Marcello M. Mariani helped me in devising and developing the research design, formulating the research questions, selecting the right methods and applying them correctly, interpreting the results and further developing the theoretical contributions and practical implications, and revising the entire manuscript prior to submitting it to a conference and later to a journal.

I confirm that Paper 2 (**Chapter 3** of the thesis) was co-authored with my 1st supervisor Professor Marcello M. Mariani. My overall contribution as a lead author is 65%. Professor Mariani provided critical guidance during the conception of the work, the literature review process, the research design, the theoretical contributions, and revised the entire manuscript prior to submitting it to a journal.

I confirm that Paper 3 (**Chapter 4** of the thesis) was co-authored with my 1st supervisor Professor Marcello M. Mariani. My overall contribution as a lead author is 70%. Professor Mariani has provided critical guidance on framing critically the theoretical underpinnings of the work, its positioning into relevant literature, the empirical analyses, the theoretical contributions, and revising the entire manuscript prior to submitting it to a journal.

Acknowledgement

This thesis makes the end of an important chapter of my professional and personal life. This learning journey has profoundly affected the person I have become. As such, writing this acknowledgment section is a truly emotional moment.

First of all, I would like to thank my first supervisor Professor Marcello M. Mariani. I am grateful you have encouraged me to pursue a PhD in such a fascinating and novel topic, like the 4th Industrial Revolution. Thank you for the constant support, pastoral guidance, and mentorship you have provided throughout my PhD. I have absorbed a lot of direct knowledge from you on how to conceive, design, and conduct meaningful academic research. Besides, your dedication, leadership and profound knowledge of the scientific publication formal and informal processes has been crucial to achieving publication of the research outputs mentioned in this thesis. I could have not asked for anything better. I also appreciate the full support of my second supervisor, Professor Maksim Belitski during the important stages of my PhD.

I also would like to thank the Department of Leadership, Organisations and Behaviour of Henley Business School for believing in me and awarding a scholarship for my doctoral research. I am grateful to Professor Andrew Godley, Head of the department, for allowing me to enrich my knowledge as a researcher and educator, participating to a wide range of training events and conferences. I still remember our first meeting when you depicted the PhD as a transformative journey that would have significantly impacted my personal growth. Only now I can fully appreciate how true your words were. I am also thankful to Professor Yelena Kalyuzhnova, our Postgraduate Research Director, for having established with me, as the PhD Rep, a fruitful collaboration to constantly improve the communication between the academic staff and PhD students by actively listening to the voice of our PhD community. Besides, your teaching insights truly level up my self-confidence at the beginning of my teaching assistant duties. I am also grateful to Dr. Lebene Soga, who has been my very first teaching role model. I found your guidance and support invaluable in developing my own teaching practices and constantly striving to enhance the student experience. Thank you for the stimulating discussions and for always helping me when I was stuck with challenges in the classroom.

During my PhD journey I never felt alone but part of a wider community. I am thankful to Tian for accompanying me during my first visit to Henley Business School and introducing me to our PhD community. I am also grateful to Parisa for sharing useful teaching tips and Wendy, the best module co-convenor I could have asked for. However, my sincere thanks go to all my colleagues with whom I shared part of this journey that would have not been so enjoyable without you Ana, Andrea, Chengcheng, Dalila, Daniyar, Fabio, Federica, Giuseppe, Irakli, Kirsty, Mads, Matthew, Melanie, Natalya, Niloo, Rodrigo, and Tommaso. Nonetheless, I never missed the support from where I come from. Thank you Francesca, Lucia, and especially Marco, my best friend, for supporting me while abroad and always be there for me when coming back home. I really appreciate it.

My special thanks to Katiuscia. We met when you were finishing your PhD and we almost shared mine entirely. From a privileged point of view, you supported and challenged my thinking in your own special way. Simply, It would have not been the same without you.

Last, but not the least, thanks to my Family that has supported me in every decision of my carrier, has seen me struggle during the path but has always had that word of comfort to keep me going, stronger and more confident than before. It does not matter where I am in this world, you are always with me.

Papers included in the thesis

This thesis is presented as a collection of papers. It comprises of the following original works that have been published or under review. The papers were all developed and written during my enrolment in the PhD in Management at the Department of Leadership, Organisations and Behaviour, Henley Business School, University of Reading, 2018-2020.

Publications related to Chapter 2

A refined version of **Chapter 2** has been presented after enhancement and revision of my first supervisor, Professor Marcello M. Mariani at the 10th INEKA Conference: "*Knowledge, Business, and Innovation. Economies and sustainability of future growth*" in June 2019. The paper was later submitted to an academic journal and led to the publication of the following journal article in a 3* ABS journal:

- Mariani, M.M., & Borghi, M. (2019). Industry 4.0: A bibliometric review of its managerial intellectual structure and potential evolution in the service industries. *Technological Forecasting and Social Change*, 149, article number 119752.

Publications related to Chapter 3

A reduced version of **Chapter 3**, after revisions of my first supervisor, Professor Marcello M. Mariani, has been published in the form of a research note in a 4* ABS journal:

- Borghi, M., & Mariani, M.M. (2020). Service robots in online reviews: online robotic discourse. *Annals of Tourism Research*, article number 103036.

Besides, an extract of the research has been presented by my first supervisor Marcello M. Mariani and me at the AIRSI2020 Conference "*Artificial Intelligence & Robotics in Service Interactions: trends, benefits, and challenges*" organized online in September 2020 by the University of Zaragoza, Spain.

Remarks related to Chapter 4

Chapter 4, despite not having been published yet, is under review with a leading 4* ABS journal.

The 4th Industrial (R)evolution:
the role of service robots in online discourse

Abstract of the PhD thesis

The 4th Industrial Revolution is expected to profoundly change the contemporaneous society. Despite rising in the manufacturing industries, by the name of Industry 4.0, business leaders are increasingly turning their attention towards services and service industries. Scholars in management and social sciences have started to conduct their examinations; however, the emerging intellectual structure of this nascent field of literature has never been synthesised. Moreover, little is known about the role of Industry 4.0 initiatives in the service industries since no study so far has critically analysed the service component of this disruptive phenomenon. In particular, in the literature pertaining to the digital transformation of services, the infusion of artificial intelligence in service robots – one of the technological pillars of Industry 4.0 – is perceived as a crucial source of innovation, able to redefine the service experience, especially in the tourism domain. However, there is no empirical evidence, in the post-service consumption phase, that sheds light on the peculiarities of service robots and most notably on their influence on perceived overall service quality and customer satisfaction.

To bridge the abovementioned research gaps, this thesis demonstrates that (**a**) the managerial and social sciences intellectual efforts related to Industry 4.0 can be effectively classified in seven distinctive communities (**Chapter 2**); however, (**b**) services and the service industries are an unexplored but valuable component of the Industry 4.0 phenomenon (**Chapter 2**); (**c**) within the service industries, service robots, through the analysis of online conversations, are perceived as a popular and distinctive attribute in guests' evaluation of the stay (**Chapter 3**); and (**d**) they are able to positively impact the customer experience and perceived service quality (**Chapter 4**).

Taken together, these findings suggest that digital transformation, in the age of the 4th Industrial Revolution, does not only promise productivity gains in the manufacturing industries but also has the capability to improve the customer experience and perceived service quality within the service industries.

Keywords: Industry 4.0; Fourth Industrial Revolution; Services; Service industries; Service robots; Online Reviews; Customer Satisfaction.

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Chapter 1: Introduction

"*Then you don't remember a world without robots. There was a time when humanity faced the universe alone and without a friend. Now he has creatures to help him; stronger creatures than himself, more faithful, more useful, and absolutely devoted to him. Mankind is no longer alone. Have you ever thought of it that way?*"

Isaac Asimov, (1950: p. xiv), *I, robot*. Garden City, NY: Doubleday & Company.

An unprecedented innovation wave, seamlessly linking the digital, physical, and biological domains, is providing the foundations of the 4th Industrial Revolution. Emerged to sustain the economic development of the manufacturing industries, by the name of Industry 4.0, this socio-technical process is supposed to have a broader impact on different industries and spheres of human life. Yet, in extant academic literature, by the time I started my PhD, little was known about the emerging intellectual structure of the managerial and social sciences stream of research revolving around the phenomenon. In light of this remarkable research gap, **Chapter 2** of this thesis, through a systematic quantitative literature review approach combined with network analysis and bibliometric techniques, aims to enhance scholarly knowledge by providing a clear structural image of the research domain. However, practitioners and business leaders are increasingly emphasising the importance of services and the service industries as a future prominent component of the revolution. It is worthwhile noticing that Germany, which has pioneered the revolution in the manufacturing industries, with its *Industrie 4.0* plan, has now shifted its focus toward services with the *Smart Service World* initiative. Nonetheless, no study so far has tried to critically analyse how and to what extent scholars in management are addressing the Industry 4.0 phenomenon in the service industries. Therefore, the entire body of managerial knowledge gathered in **Chapter 2** is also uniquely analysed paying particular attention to the role of the service component of Industry 4.0 initiatives. Since through these initial investigations services and the service industries resulted in an unexplored but valuable component of the new industrial revolution, I decided to target my intellectual effort towards this specific industry for the following chapters of the thesis.

Delving deeper in the literature pertaining to the digital transformation of services, scholars seem to suggest that the main source of innovation is provided by the infusion of artificial intelligence in machines, under the guise of service robots. This is because a physical embodiment coupled with a high level of agency allows this form of innovation to effectively interact with the service customer and be perceived as a social agent. Therefore, service robots can completely redefine the service experience and especially the tourist experience. Indeed, service robots can have a disruptive effect in a high-touch service context, such as the tourism and hospitality one. Understanding the impact of service robots in this domain is even more compelling due to the difficulties that historically managers have experienced to efficiently innovate. For these reasons and because they are considered a remarkable example of the introduction of service robots in the tourism and hospitality landscape, hotel companies have been taken into account as the empirical setting of **Chapters 3** and **4**. However, the literature related to service robots is rather fragmented, highly conceptual, and lacks empirical evidence, most notably in the post-service consumption phase. Accordingly, in **Chapter 3** a novel means to track the diffusion and adoption of service robots is conceived, by the name of *online robotic discourse* - defined as electronic Word-Of-Mouth (eWOM) in online reviews mentioning explicitly service robots deployed in hospitality services. Differently from surveys and laboratory experiments, online conversations are considered a more reliable, less prone to sampling bias, and abundant source of information. Thus, **Chapter 3** conducts an exploratory analysis of *online robotic discourse*, deploying a data science approach, to understand whether service robots are a popular and distinctive feature in guest's evaluation of their hotel stay.

Yet, customer satisfaction is perceived to be the key to the success of tourism and hospitality companies. Indeed, there is a perennial tourism and hospitality scholars' quest for unveiling which attributes of the service offering are more appreciated by service customers. Nonetheless, empirical large-sample investigations on the influence of service robots on perceived overall service quality and customer satisfaction are virtually non-existent. This is surprising, not only for the paramount importance of customer satisfaction but also because the deployment of service robots can potentially generate a trade-off between productivity and service quality. To bridge this gap, **Chapter 4**, rooted in the three-factor theory of customer satisfaction and the concept of *online robotic discourse*, aims to investigate the impact of service robots' performance on perceived customer satisfaction, under the guise of online review ratings. It does so leveraging on penalty-reward contrast analysis built upon text analytics techniques, on a sample of 44 international hotels pioneering the introduction of service robots in companies' operations. Besides, further robustness checks deploying a quasi-experimental research design, through propensity score matching, validate the study's findings.

Overall, the aim of this PhD thesis is to enrich scholarly knowledge related to the phenomenon of the 4th Industrial Revolution, and understanding to what extent service robots – one of the key technological pillars of Industry 4.0 – impact the customer experience within the service industries through the analysis of online conversations.

Accordingly, the body of knowledge developed in this PhD thesis (**Chapters 2, 3** and **4**) aims to provide an answer to the following research questions:

a) *What is the intellectual structure of recent/emerging managerial and social sciences literature related to Industry 4.0?* (**Chapter 2**)

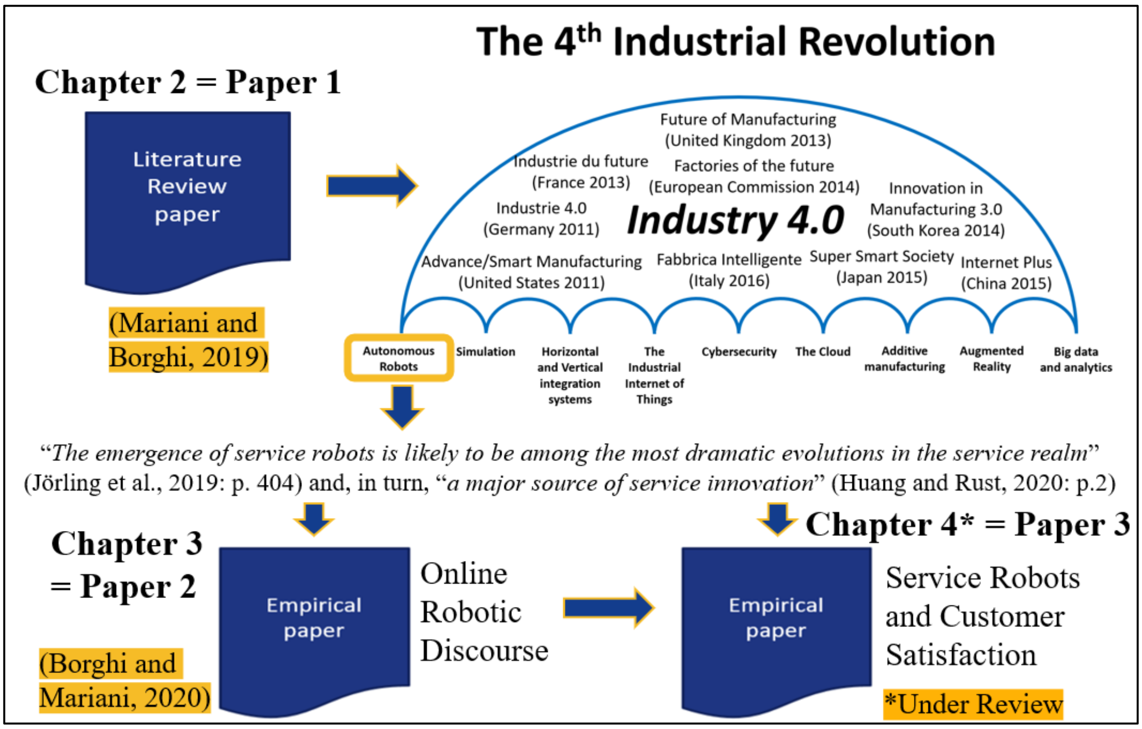
b) *How and to what extent are management scholars addressing the Industry 4.0 phenomenon in the service industries?* (**Chapter 2**)

c) *Are service robots becoming an increasingly distinctive and popular feature in hotel-related eWOM beyond their introduction?* (**Chapter 3**)

d) *To what extent do service robots influence perceived customer satisfaction in the hotel industry?* (**Chapter 4**)

Figure 1 provides an overview of the entire PhD thesis, linking the different chapters graphically.

Figure 1. *Graphical Abstract of the Thesis*



Finally, **Chapter 5** provides a throughout overview of the contributions stemming from this thesis, especially highlighting the theoretical and methodological contributions, practical implications, limitations, and a research agenda for future scholars.

Chapter 2: Paper 1.

"Industry 4.0: A Bibliometric Review of its Managerial Intellectual Structure and Potential Evolution into the Service Industries"

Abstract

An unprecedented transformation involving the fusion and interaction between the physical and digital domains is taking place in the realm of manufacturing, in the form of the "Industry 4.0". In its broad conceptualization, this innovation wave is supposed to influence almost every aspect of businesses' value chain, and our society, under the guise of the 4th Industrial Revolution. For this reason, also social sciences and management scholars have started doing research on the phenomenon. However, so far, the overarching intellectual structure emerging from this new stream of literature has not been critically discussed. Furthermore, despite being part of the rhetoric in several industrial governmental plans little is known about the service component of Industry 4.0 initiatives. Thus, the aim of the study is to fill these gaps by leveraging on a systematic literature review approach. We use a data-driven approach and methodology, embedding both bibliometric and network analysis techniques to provide a clear visualization of the emerging intellectual structure in social sciences and management studies related to the Industry 4.0. Besides, we develop a conceptual framework based on the most recurrent themes emerging from the bibliometric and network analysis results. As service businesses can create and capture value generated through the 4th Industrial Revolution as well as manufacturing firms, we suggest that scholarly attention should also be directed toward the service industries and provide a research agenda.

Keywords: Industry 4.0; Fourth Industrial Revolution; Services; Systematic Literature Review; Bibliographical Coupling; Social Network Analysis.

2.1 Introduction

Nowadays, our society is witnessing the emergence of an uncontrollable innovation wave in a wide range of fields. In its broadest connotation, the phenomenon has been labelled by several scholars and practitioners as "*the fourth industrial revolution*" (European Commission, 2016b; Kang et al., 2016; Liao et al., 2017; Schwab, 2016; Skilton and Hovsepian, 2017). Specifically, it is a socio-technical process that is affecting the physical, digital and biological domains, based on the innovative and effective exploitation of a wide range of new and emerging prevalently digital technologies through their fusion and interaction (Schwab, 2016). Even though part of the practitioners community has considered this process just as a natural evolution of the third industrial revolution (Drath and Horch, 2014; O'Halloran and Kvochko, 2015; Syska and Liévre, 2016), undeniably digital transformation is disrupting entire sectors and industries with the emergence and development of new business models relying significantly on digital technologies (Geissbauer et al., 2016). Furthermore, academics are forecasting the outcomes of such an industrial shift while it is actually occurring (Gilchrist, 2016).

The watershed event that triggered this "revolution" took place at the Hannover Fair in 2011, when the German government announced for the first time its plan "Industrie 4.0" to safeguard the long-term competitiveness of its national manufacturing industry (Hermann et al., 2016), which can be considered as the ancestral label of the 4th industrial revolution confined to the manufacturing sector (Skilton and Hovsepian, 2017). If we rely on the original definition: "*In essence, Industrie 4.0 will involve the technical integration of Cyber Physical Systems (CPS) into manufacturing and logistics and the use of the Internet of Things and Services in industrial processes*" (Kagermann et al., 2013: p. 14). The outcomes would be "*implications for value creation, business models, downstream services and work organisation*" (Kagermann et al., 2013: p. 14). In light of a critical reading of the aforementioned statement by Kagermann et al. (2013), and observing a dearth of studies explicitly exploring the managerial impact of the Industry 4.0 phenomenon, the aim of this manuscript is to derive and elaborate the intellectual structure of the emerging research streams related to Industry 4.0 in the wider social sciences, by reviewing extant literature in a data-driven fashion. Besides, trying to follow the evolution of the phenomena at the governmental level, we investigated if and to what extent services (and service industries) have been addressed by management scholars by adopting the perspective of the Industry 4.0. This is important because national governments play a crucial role in the promotion of innovation activities related to the new industrial revolution (Reischauer, 2018) and they are gradually changing their focus, in terms of policies, towards services and the service industries. Indeed, the German government, as a pioneer of the Industry 4.0, has put forward the "Smart Service World" plan to enhance the competitiveness of companies' business services (German Federal Ministry, 2017). Furthermore, also the practitioners' community is trying to devise how the 4th Industrial Revolution could impact the service industries. To this aim, the Boston Consulting Group has coined the term “Service 4.0” (Rehse et al., 2016), whose development is considered a top priority by the European Commission (European Commission, 2016a). Yet, despite this evidence suggesting, at least from a policymaker and practitioner perspectives, a shift of 4th Industrial Revolution’s plans toward services and the service industries, scholars in management and social sciences seem to have overlooked the potential evolution of the phenomenon. This is a remarkable research gap considering that the service industries have the highest share of Gross Domestic Product in most of the advanced economies (Buckley and Majumdar, 2018).

The study is distinctive for several reasons. Firstly, to the best of our knowledge, this is the first attempt to examine the role of services through the lenses of the Industry 4.0. Secondly, part of the novelty is also related to the methodological perspective of the study. In fact, the study leverages on a data-driven approach, which is innovative and cannot be found in existing reviews dealing with the Industry 4.0 phenomenon from a social sciences and managerial perspectives (Piccarozzi et al., 2018; Schneider, 2018). In particular, we adopted a specific bibliometric technique, namely *bibliographical coupling*, able to identify emerging research fields and streams in the relevant literature (Zupic and Čater, 2015). Furthermore, we carry out a more granular analysis leveraging a wider set of keywords and provide a clear visualization of the thematic clusters of the literature by applying a community discovery algorithm to the results of the bibliometric technique adopted. Thirdly, with the aim of providing a better understanding of the topics dealt with by management and social sciences scholars regarding the 4th Industrial revolution, we propose a conceptual framework which maps out the most substantial findings from the network structure. Fourth, based on the study’s results we provide a research agenda to guide scholars aiming to further investigate the Industry 4.0 evolution. To this end, we also highlight potential meaningful theoretical lenses and emerging disciplinary fields that researchers could use to underpin their examinations.

The manuscript is organized as follows. **Section 2.2** provides an in-depth overview of the term *Industrie 4.0* and its related initiatives highlighting the research questions addressed by the study. **Section 2.3** illustrates the research design which consists of scholarly documents collection and retrieval and methods. The latter sub-section includes an in-depth description of the bibliometric technique selected for the purposes of the study, namely *bibliographical coupling*. **Section 2.4** describes the findings, at a macro and micro level, showing the sample of papers collected and portraying each of the communities detected during the social network analysis, as well as the quantitative results related to the analysis on services. Specific guidelines for future researchers investigating Industry 4.0 initiatives and practical implications stemming from the study’s results are reported in **Section 2.5**. Finally, **Section 2.6** offers the conclusions and limitations of the work.

2.2 Industry 4.0 evolution

2.2.1 Industrie 4.0: definitions

As described by the "Industrie 4.0 Working Group" (Hermann et al., 2016; Kagermann et al., 2013) the three basic concepts underneath the *Industrie 4.0* phenomenon are: Cyber Physical Systems (CPS), Internet of Things (IoT) and Smart factories. The first allows the fusion of the virtual and physical world and is defined as the "*integrations of computation and physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa*" (Lee, 2008: p. 1). On the other hand, the term IoT, firstly introduced in 1999 (Ashton, 2009), considers "*'things' and 'objects', such as RFID, sensors, actuators, mobile phones, which, through unique addressing schemas, (…) interact with each other and cooperate with their neighbouring 'smart' components, to reach common goals*" (Giusto et al., 2010: p. v). These two concepts are very close to each other, even if they have emerged in two different epochs; however, the CPS definition seems to embrace a broad range of application fields (Gilchrist, 2016). Finally, combining the notions of IoT and CPS and placing them inside the working space, especially in its operations, has brought to life the concept of Smart Factory, defined "*as a factory that context-aware assists people and machines in execution of their tasks. This is achieved by systems working in background. […] These systems accomplish their tasks based on information coming from the physical and virtual world. Information of the physical world is for instance the position or condition of a tool, in contrast to information of the virtual world like electronic documents, drawings and simulation models. […]*" (Lucke et al., 2008: p. 116).

By refining the early definition of "Industrie 4.0", and embracing also the English translation "Industry 4.0" which emphasis the nature of the phenomenon more as a "new paradigm", Hermann et al. (2016: p. 1) define it as "*the convergence of industrial production and information and communication technologies*". More specifically, taking into account the technical side of the phenomenon, the Boston Consulting Group (Rüßmann et al., 2015) identify nine foundational technologies that will act as enablers of the Industry 4.0 ecosystem. These nine pillars of technological advancement encompass: autonomous robots, simulation, horizontal and vertical integration systems, industrial IoT, cybersecurity, cloud, additive manufacturing, augmented reality, big data and analytics. Despite some of these technologies being already used in manufacturing (Rüßmann et al., 2015), the real disruption in the production lines will occur following the "Industry 4.0 design principles" highlighted by Hermann et al. (2016). The authors, among the first to notice a lack of academic effort to describe the revolution, leveraging on design theory, refer to interconnection, technical assistance, decentralized decisions and information transparency as the constituents of the phenomenon (Hermann et al., 2016). This process will allow the production line to change from isolated and optimized cells to fully integrated data and production flows across borders (Rüßmann et al., 2015). Ultimately, the unprecedented connection of people, machines and data will make possible to fuel the idea of the *Internet of Everything* (see Hermann et al., 2016).

Embracing an institutional theory perspective (Meyer and Rowan, 1977; DiMaggio and Powell, 1983), very few studies (Kim, 2018; Reischauer, 2018) argue that the Industry 4.0 is actually a "meso" revolution since applying the long wave theory (Kondratieff, 1935; Schumpeter, 1939; Ayres, 1990) to the phenomenon under investigation faces several limitations. Although it is beyond the scope of the present paper to discuss the identity of the Industry 4.0, we deploy these precious insights in the discussion section to unpack the theoretical lenses that could be more suitable to further analyse the phenomenon in the services industries.

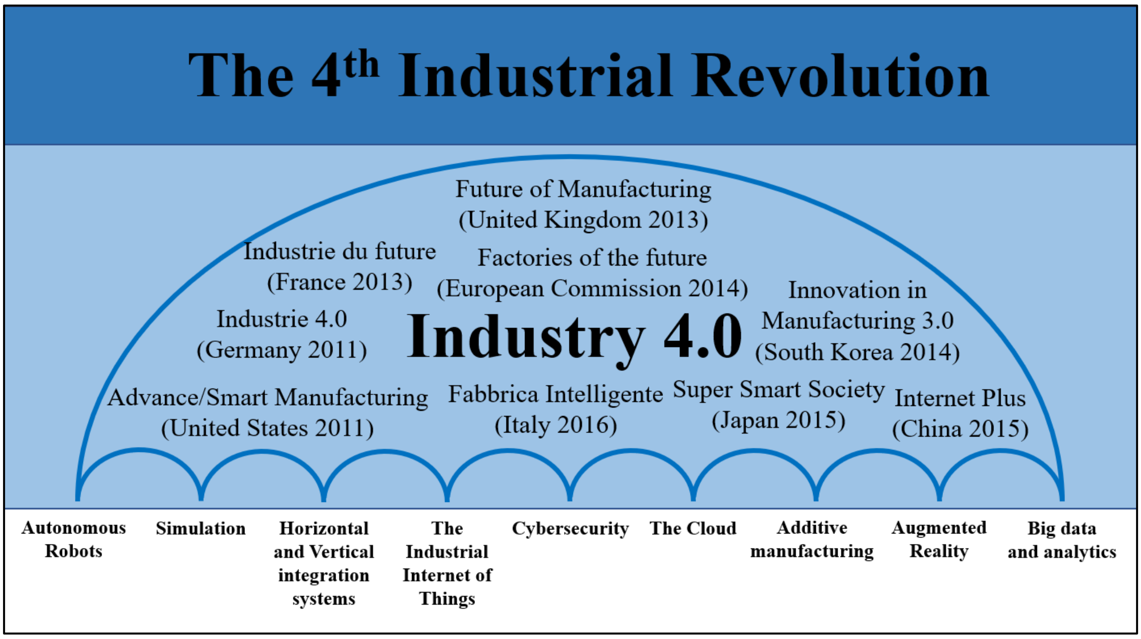
2.2.2 Industry 4.0 plans and strategies

The transformation wave, in the realm of manufacturing, brought about by the "Industrie 4.0" initiative promoted by the German government has given rise to many other governmental and industrial plans embracing the same principles and technologies in order to enhance manufacturing performance (Ridgway et al., 2013). At the same time of Germany, the United States developed the "Advanced Manufacturing Partnership" initiative in 2011 that established the Advanced Manufacturing National Program Office in 2012 which in its turn is supporting the "Smart Manufacturing Innovation Institute". In Europe, France presented the plan named "La Nouvelle France Industrielle" in 2013 as an antecedent of the "Industrie du future". In the same year, the United Kingdom announced the "Future of Manufacturing" plan which aims to support the growth of UK manufacturing over the next decades, replacing the "High-value manufacturing strategy 2012 to 2015" previously introduced by the UK government for accelerating UK economic growth through the use of high-value manufacturing. In the old continent, The European Commission launched the "Factories of the Future" programme, a new contractual Public-Private Partnership, which has been followed, in 2017, by the Italian national plan "Industria 4.0" supported by the Italian Ministry of Economic Development to boost the investment in new technologies, research and development, and revitalise the competitiveness of Italian companies. If we look at other continents, Asia "first mover" was the South Korean government which in 2014, through the "Innovation of Manufacturing 3.0" plan, decided to catalyse Korean manufacturing efforts on defined innovation strategies (Kang et al., 2016). Subsequently, the same route has been taken by the Chinese and Japanese governments that promoted respectively the "Made in China 2025" (and the "Internet Plus") plans and the "Super Smart Society" plan in 2015 (Liao et al., 2017). Finally, the Singapore government announced in 2016 its "Research, Innovation and Enterprise 2020 Plan" to spread key principles in the advanced manufacturing and engineering domain.

Alongside governmental plans, a wide range of industrial strategies have also been developed by companies involved in paving the way to the 4th Industrial revolution. In particular, AT&T, Cisco, General Electric, IBM and Intel founded conjointly the "Industrial Internet Consortium" in 2014. The aim of this initiative was to better organise and coordinate the priorities and enabling technologies of what has been labelled as the "Industrial Internet", term coined by General Electric with similar technical basis but with further application domains than the original plan "Industrie 4.0" (Drath and Horch, 2014).

With the aim of constructing a conceptual graphical representation of the phenomenon under investigation, in **Figure 2** we illustrate the "Industry 4.0" as an umbrella term which has been supported by a wide range of government plans, whose ecosystem is characterized by 9 reference "pillar" technologies (those proposed by Rüßmann et al., 2015). In our graphical representation, the 4th Industrial Revolution constitutes an overarching circumlocution conceptually encompassing the Industry 4.0 (Schwab, 2016).

Figure 2. *Authors' graphical representation of the 4th Industrial Revolution*



2.2.3 From Industry 4.0 to Service 4.0

The strategies and plans concerning the adoption of the "Industry 4.0" principles described in the previous subsection have not only a regional/national flavour (Geissbauer et al., 2016), but are also mainly related and confined to the manufacturing industry. However, this phenomenon is not circumscribed to the manufacturing sector and business leaders believe that it will increasingly also involve the service industries (European Commission, 2016a; Rehse et al., 2016). An effective service innovation will not just benefit the service providers in terms of efficiency and effectiveness, but also services customers in terms of opportunities to receive improved services including new and improved features and attributes (European Commission, 2016a). Indeed, as stated at the opening speech at the Stakeholder conference on the Services (European Commission, 2016a), in order to be able to deliver Industry 4.0 values, services need to display a high level of digitalisation as well. This implies having a modern, efficient, and cross-border services market. Accordingly, in the era of Industry 4.0, the Boston Consulting Group (Rehse et al., 2016) coined the term Service 4.0, which is a collective term of technologies and concepts of service and support function organizations, based on new disruptive technologies (European Commission, 2016a). Besides, it allows companies to share open infrastructures and to deliver services through multiple channels in a proactive and truly customized way (Rehse et al., 2016).

At this stage, the governmental efforts on this direction still lack policies and plans which can act as propulsor of investments for an efficient service innovation. Only the German government, within the High-Tech Strategy 2020 Action Plan, announced the "Industrie 4.0" successor "Future Project": the "Smart Service World – Internet-based services for the economy" (German Federal Ministry, 2017). Related to business services, this is a pilot plan which is providing fundings for 20 selected high-tech service projects with the goal to make Germany the digital lead provider of smart services of the future. The German government vision lies on a new hybrid service economy, where products and online services are merged to become "Smart Services". This disruptive shifting in the business economy paradigm will be driven by digital transformation on the global economy (German Federal Ministry, 2017). This first initiative promoted by the German government (which has already reached its second stage "Smart Services II"), as in the case of the "Industrie 4.0", sheds light on what business leaders will presumably focus on in the future: the service industries. Thus, due to the critical function associated with governmental plans to encourage and boost investments in Industry 4.0 projects (Kim, 2018; Reischauer, 2018), a question arises naturally: "will the service industries become the next application context and setting of the 4th Industrial Revolution?". Addressing this question is particularly important as industry reports suggest that the digital transformation of service industries is particularly promising as today services account for the highest share of the total Gross Domestic Product in most of the advanced economies and they are becoming increasingly vital to countries' economic growth (Buckley and Majumdar, 2018).

Nonetheless, this potential shift of the revolution is intrinsically related to the emergent stream of academic literature in the service realm that addresses the digital transformation of services (Rust and Huang, 2014) where artificial intelligence is seen as the game-changer technology (Huang and Rust, 2018; 2020). Indeed, artificial intelligence able to learn, connect and adapt could be a major source of innovation in the service domain (Huang and Rust, 2020), especially when infused in autonomous machines (Jörling et al., 2019). In particular, it seems that intelligent robots have the capabilities not only to further automate service processes, but also to redefine the way value is created during the service experience (Larivière et al., 2017). Yet, service and marketing scholars have only recently loosely linked the digital revolution to the 4th Industrial Revolution (i.e., Huang and Rust, 2018). The latter has mostly been used as a fancy locution, without fully exploring its meaning. As such, making sense of how and to what extent scholars in management and social sciences are addressing the Industry 4.0 phenomenon in the service industries will allow scholars to build a joined up body of knowledge revolving around the 4th Industrial Revolution.

In fact, to date, a limited number of studies in the management field have tackled the role that digital transformation might play within the service industries for creating and exploiting novel business opportunities through new business models, building a sustainable competitive advantage, and improving customer engagement and satisfaction (Nambisan, 2017). Thus, the aim of this literature review is to deeply investigate the impact of the broad meaning of the "Industry 4.0" concept, as the 4th industrial revolution, in the specific area of managerial and social sciences literature. Discerning the way, the set of emergent technologies, which enable the Industry 4.0 ecosystem, can shape the structure of the organisation and tailor its business model. In essence, the study purpose is to examine what has been explored in the managerial and social sciences literature related to the 4th industrial revolution in order to discover if this concept is paving the way for an application in the service industries.

A wide range of literature review has been realized in relation of the Industry 4.0 (Brettel et al., 2014; Chiarello et al., 2018; Galati and Bigliardi, 2019; Liao et al., 2017; Lu, 2017; Xu et al., 2018) or one of its core concepts, such as smart factory (Strozzi et al., 2017) and smart manufacturing (Kang et al., 2016; Lu and Weng, 2018). However, just the studies of Piccarozzi et al. (2018) and Schneider (2018) try to explore the managerial side of the phenomenon through a systematic literature review methodology. The former tried to define the Industry 4.0 from a managerial point of view highlighting main topics and avenue of future research, just considering the keyword "Industry 4.0". Whereas the latter using a wide range of keywords sheds light on the future managerial challenges link to the Industry 4.0, analysing documents published until 2016 in German and English. However, transcending from the set of utilised research terms, to the best of our knowledge no study has tried to assess the intellectual structure of the emerging managerial and social sciences literature related to Industry 4.0 relying exclusively on a data driven approach. Moreover, no one, so far, has investigated the role of services through the lenses of the Industry 4.0.

More specifically, the manuscript aims to address two distinct research questions:

1. *What is the intellectual structure of recent/emerging managerial and social sciences literature related to Industry 4.0?*
2. *How and to what extent are management scholars addressing the Industry 4.0 phenomenon in the service industries?*

2.3 Research Design

Since 2011, when the German government gave birth to the term “Industrie 4.0”, the literature related to this socio-economic and technological phenomenon has grown exponentially (Hermann et al., 2016; Liao et al., 2017). In order to provide an objective overview of its impact on the managerial literature, the paper adopts a *systematic quantitative literature review* method (Tranfield et al., 2003), which is largely embraced by the social sciences community (Mariani et al., 2018a; Mura et al., 2018). A *narrative literature review* method could have been perceived as more subjective (Cipriani and Geddes, 2003), susceptible to difficulties in data reproduction (Hart, 2018) and not involving an exhaustive quantitative analysis (Pickering and Byrne, 2014).

After having retrieved the initial collection of documents, with the aim of identifying the emerging trends in the 4th industrial revolution literature, we performed a bibliometric technique, namely *bibliographical coupling*. This bibliometric method has been found to be the most suitable to map novel streams of literature in an emerging field (Boyack and Klavans, 2010). Subsequently, we qualitative analysed the full text of each retrieved document to assess the role played by services in the Industry 4.0 landscape.

2.3.1 Documents’ Collection

The initial concept of “Industrie 4.0” has been embedded in many governmental and industrial plans, which have developed a new set of specific keywords with the aim of guiding the 4th Industrial revolution. Even scholars, trying to clarify the scope of Industry 4.0, have identified new possible synonymous of the Industry 4.0 notion. Thus, in order to collect the most comprehensive set of papers related to this new industrial revolution (Hermann et al., 2016; Liao et al., 2017; Möller 2016), the research query embedded a list of keywords related to “Industry 4.0” and all its facets. Any search string has been combined with the “OR” operator to create the final research string. **Table 1** contains all the terms related to “Industry 4.0” integrated in the research query, divided by their country of origin (which introduced a governmental plan), organizations (which coined the term) and scholars (who stated different synonymous).

Table 1. *Industry 4.0 Keywords*

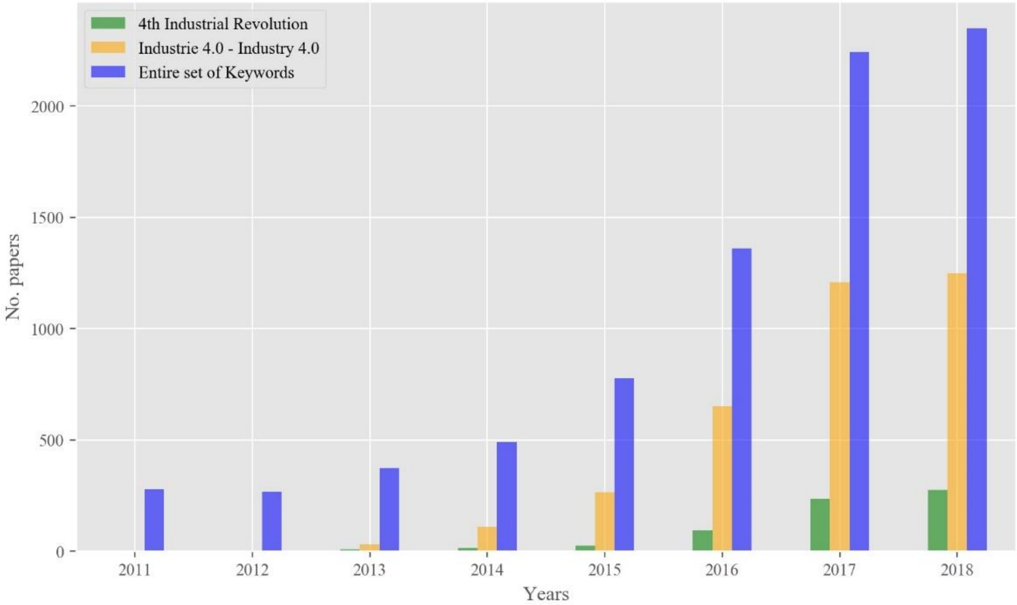
Nations	**Industry 4.0 keywords**
Germany	Industrie 4.0, Industry 4.0
US	Smart Manufacturing, Advanced Manufacturing
France	Industrie du future
United Kingdom	High value manufacturing, future of manufacturing
European Commission	Factories of the Future, Factories 4.0
South Korea	Manufacturing 3.0
China	Made in China 2025, Internet Plus
Japan	Super Smart Society
Italy	Industria 4.0, Fabbrica Intelligente, Impresa 4.0
Organizations	
General Electric	Industrial Internet

Scholars	
Liao et al. (2017)	Fourth industrial revolution, 4th industrial revolution
Möller (2016)	Digital manufacturing
Hermann et al. (2016)	Integrated Industry, Smart Industry
Schneider (2018)	Smart Factory, Production 4.0

The electronic database chosen to retrieve indexed articles was Scopus (https://www.scopus.com), founded by Elsevier, which is considered, alongside Web of Science, the most prominent source of academic works in the social sciences domain (Vieira and Gomes, 2009). Moreover, in the last few years, Scopus has consistently been found to have greater overall coverage of academic journals than Web of Science (Mongeon and Paul-Hus, 2016; Waltman, 2016). However, Scopus, as depicted by Strozzi et al. (2017), in their literature review about the "Smart Factories", presents data not formatted in a homogeneous manner, especially in the reference list. Despite this technical issue and being largely neglected by management scholars (Zupic and Čater, 2015), we decided to retrieve the articles for our literature review study from this electronic database in order to exploit its great potentiality in terms of coverage. To date, Scopus englobes more than 5'000 publishers and more than 22'800 serial titles that lead to approximately 70 million of indexed items (Scopus, 2019).

Exploring the whole range of publications related to the subject under investigation, seeking for one of the keywords related to the Industry 4.0, in either the abstract or title or keywords of an item in the database, without selecting any constriction criteria, the search query returned 11,716 documents. The items broke down to 3610 and 675, just considering the terms "Industry 4.0" or "Industrie 4.0" on one side and "4th industrial revolution" or "fourth industrial revolution" on the other side, respectively. As shown in **Figure 3**, the literature related to the Industry 4.0 has been growing faster, especially in the last few years, presenting almost an exponential growth. Moreover, the graph depicts a significant difference in terms of number of items among the three categories analysed. In particular, the amount of publications considering the entire set of keywords related to the Industry 4.0 is almost twice the amount of the items retrieved just considering the terms "Industry 4.0" or "Industrie 4.0". In fact, for example United States scholars could have referred, in their publications, to the concept of Industry 4.0 using the term "advanced manufacturing" (Reynolds and Uygun, 2018) introduced by the United States government with the same principles of the Industry 4.0 one. This was a symptomatic clue for our reasoning, which led us to consider a wide range of keywords to collect the initial set of papers.

Figure 3. *Overall publication trend Industry 4.0*

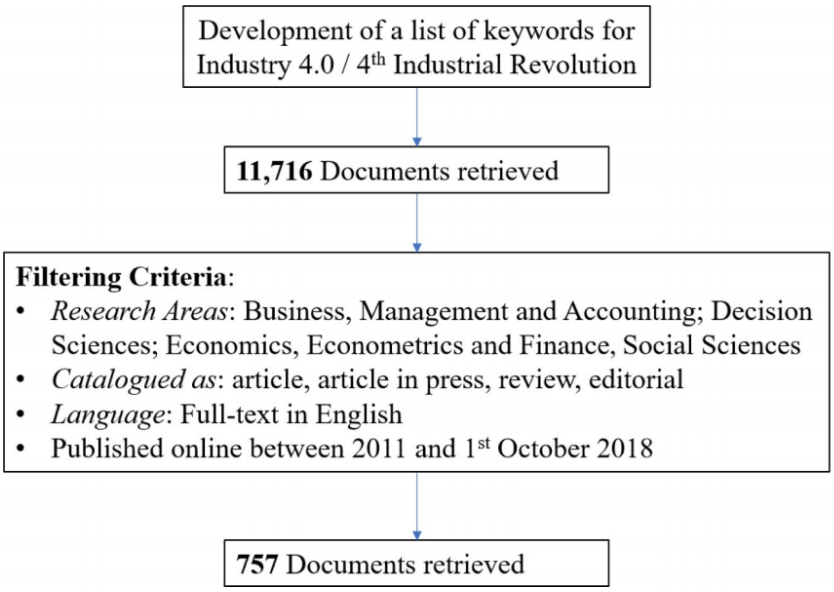


During the refining process of the literature review we adopted several criteria to focus on the research articles related to the objective of our study. Thus, from the search query we retrieved items which:

1. Include one of the terms in the defined set of keywords related to the Industry 4.0 in either their abstract or title or related keywords.
2. Belong to one of the selected subject areas:
    a. Business, Management and Accounting
    b. Decision Sciences
    c. Economics, Econometrics and Finance
    d. Social Sciences
3. Have been catalogued as:
    a. Article
    b. article in press
    c. review
    d. editorial
4. Have been written in English
5. Have been published after 2011, when the German government and the United States one announced their first governmental plan related to the 4th industrial revolution and available in the online database before the 1st October 2018.

Following the highlighted criteria, the electronic database returned 757, which were identified as potentially eligible items for our study. This collection of documents contained 30’349 references to 25’672 different sources. **Figure 4** illustrates the data retrieval process.

Figure 4. Data retrieval process

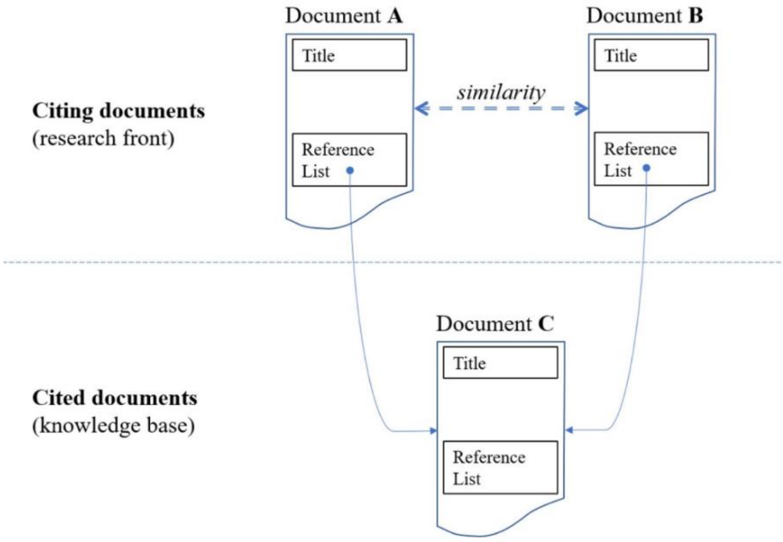


2.3.2 Method

Since the aim of the paper is to identify emerging streams of literature embracing the concept of Industry 4.0, analysing them and classifying the main findings in the most objective manner, the data analysis was conducted through the use of bibliographic coupling. This bibliometric method, able to construct the structural image of a scientific field, is the most suitable to map current research fronts (Small, 1999; Zupic and Čater, 2015). Despite being widely neglected by managerial scholars, in favour of more mainstream methods, such as co-citation analysis, it seems to have great potential in the management domain as depicted by Zupic and Čater (2015) in their survey on the use of bibliometric methods in management and organization research domain. Moreover, in recent years, it has been proven to be more effective and accurate than co-citation analysis in representing a research front (Boyack and Klavans, 2010).

In essence, bibliographical coupling infers the similarity between two documents as the degree of overlap of their reference lists. In other words, the number of shared references between two documents represents the measure of similarity between them (Kessler, 1963). Thus, this implies that the greater the number of shared records in the reference lists, the stronger the connection between to analysed documents. **Figure 5** graphically captures the similarity mechanism underpinning the bibliographical coupling analysis. In the scope of this bibliometric technique, the authors of the retrieved documents are actually the ones who decide which kind of document to cite and to link theirs to, thus, the connection captured by bibliographic coupling is guided by authors' willingness (Zupic and Čater, 2015). Therefore, unlike co-citation, bibliometric coupling is immediately available and can include new publications that have not been cited yet, since the reference list is static during the years. However, since citation habits change over time, having a limited timeframe is a critical success factor to obtain the best performance for bibliographic coupling (Glänzel and Thijs, 2011). Accordingly, as the "Industry 4.0" was formally introduced in 2011, with a recorded exponential growth in literature after 2015 (see **Figure 3**), we believe that the aim of our study fits perfectly with the use of bibliographical coupling since we aim to analyse a phenomenon that has just taken place in the last few years, whose structural image as research field is still blurred in the management literature.

Figure 5. *Authors' representation of Bibliographic coupling adapted from Garfield (2001) and Vogel and Güttel (2013)*



Bibliographical coupling, as other bibliometric techniques (e.g. co-citation analysis) aims to extract meaning from the reference list of each analysed document (Kessler, 1963). Thus, having a homogeneous formatted citation list is crucial to performing a robust bibliographical coupling analysis leading to meaningful results. As a result, we started the bibliometric analysis with a data cleaning phase, pre-processing the data included in the reference list of each analysed document. At this stage of the process, like other authors (e.g., Strozzi et al., 2017), we found many inconsistencies in the citation references of the data retrieved from Scopus. For example, at a macro level, the German report which first defines the Industry 4.0 (Kagermann et al., 2013) was cited in 14 different ways. However, looking more in details at the data, some records did not have an exact match due to the fact that one document reported the volume of the journal in which the article was published or the reference included the DOI of the cited document. These issues led us to try different bibliometric software widely used in other bibliometric studies (Zupic and Čater, 2015), such as, BibExcel (Persson et al., 2009), Sitkis (Schildt and Mattsson, 2006) and SciMAT (Cobo et al., 2012), in order to reduce the noise embedded in our data. Nonetheless, no one of the selected software lead us to satisfactory results, BibExcel did not have any pre-processing capability, Sitkit was able to perform just some basic data pre-processing tasks and SciMAT, the most difficult to use, despite being able to carry the whole scientific mapping analysis, allowed just to export the data through the use of (undocumented) script for further analysis.

Since the landscape of bibliometric software did not offer the right flexibility, controllability, and pre-processing capabilities, we developed our own bibliometric modules using Python. In the first step, we crafted a module to clean the data in the reference list using string similarity techniques. First, we employed Levenshtein algorithm (the one used by SciMAT) (Levenshtein, 1966) using the python library "python-levestain" (https://pypi.org/project/python-Levenshtein/0.12.0/) to address this task. However, the results, even using different validating thresholds, still contained a high amount of noise. Hence, we tried a different and more complex approach using a pattern recognition algorithm introduced by Ratcliff and Obershelp in 1983 (Black, 2004) implemented in the python library "difflib" (https://docs.python.org/2/library/difflib.html). Despite the quadratic complexity of the algorithm in the worst-case scenario, which resulted in a significative slower process than the application of the Levenshtein algorithm, the results were highly satisfactory, as illustrated later in a manual check we conducted. Having homogenised the contents of the reference list, we created a co-occurrence matrix, with 757 rows (the number of the papers retrieved from Scopus) and 25'672 columns (the number of unique different citations) inserting a placeholder if a retrieved paper has cited one of the papers in the global citation list. Multiplying this matrix for its transposal we obtained a similarity matrix made of 757 rows and 757 columns, showing in any cell, identified by two coordinates, such as x and y, the number of shared references between document x and y, being x and y two documents in the initial set of candidate papers.

To ensure robustness in the analysis previously performed with Python, the authors manually checked the number of shared documents in the reference list of 10 random articles from different publishers (45 comparisons in total), finding that the similarity index found using Ratcliff-Obershelp algorithm was exact in 42/45 comparisons (93.3% of accuracy), which outperformed Levenshtein algorithm's results that scored only the exact measure for 37/45 comparisons (82.2% of accuracy). Having built the foundations of our bibliographical coupling by creating the similarity matrix, the next step was to identify the clusters of documents related to the same research front in order to understand which kind of research streams are emerging in the managerial literature on Industry 4.0. To this end, we processed the similarity matrix through network analysis which is considered a fresh, effective and accurate approach to find subgroups in bibliometric studies (Zupic and Čater, 2015) and it has been increasingly adopted in the latest bibliometric studies (Ma et al., 2012; Mura et al., 2018; Vogel and Güttel, 2013) over more traditional approaches, such as multidimensional scaling or hierarchical clustering (Zupic and Čater, 2015).

Accordingly, we created an ad-hoc Python module to process the similarity matrix and obtain the underlying network, using the Python library Networkx (https://networkx.github.io/).

Subsequently, we applied the Louvain community discovery algorithm (Blondel et al., 2008) to produce the partitions of the entire network, by exploiting the Python library "python-louvain"(https://github.com/taynaud/python-louvain). The Louvain method, developed by Blondel et al. (2008) from the University of Louvain (the affiliation of the authors has given the method its name), takes advantage of the notion of network modularity in order to optimize, using a greedy approach, the process of dividing the entire network in sub-groups (also called clusters, modules or communities). This technique has been proven to have a high level of accuracy and it can perform the analysis in a limited amount of time even in networks with an extremely large number of nodes (Liu et al., 2012). The algorithm operates in two steps: firstly, it assigns to each node in the network a different community, then, it iterates along the entire set of clusters, trying to assign a node to a different cluster in order to maximise the modularity of the entire network. At each iteration step, it changes the community of the node with the one producing the greatest increase in terms of modularity (Blondel et al., 2008).

Since the Louvain algorithm assigns a community to each node in the network, the main drawback of this technique is related to the fact that the important items need to be filtered beforehand (Zupic and Čater, 2015). Thus, the authors adopted an iterative approach, applying the selected community discovery method to a wide range of networks obtained using different coupling thresholds in order to identify the one which was able to ensure a complete yet parsimonious set of results (Mura et al., 2018). Being the visualization phase, in the mapping of a scientific field through its network structure, a crucial process (Zupic and Čater, 2015), we decided to visually inspect the effectiveness of a series of mapping algorithms. To perform this task, we processed the network data, in the forms of geometric coordinates, in Gephi (https://gephi.org), an open-source network analysis software with remarkable visualization capabilities (Bastian et al., 2009). After an in-depth examination of the results provided by the algorithms built in the software, we decided to create all the graphical representations presented in **Section 2.4.2** (see **Figures 9**, **10**, **11**, and **12**) by leveraging on the Force Atlas algorithm.

Finally, to depict the clearest structural image of the topic under investigation we interpreted qualitatively and quantitatively all the clusters found using the community-discover algorithm (Mura et al., 2018). On the one hand, we analysed in-depth every single node of the network through its full text with the aim of discerning the contents and topics of each community. On the other hand, we examined the underlined structure of each sub-group, exploiting measures widely used in complex network analysis, such as density, average degree, betweenness centrality, and shortest path length (Barabási, 2016).

Regarding the second research question related to the extent to which management scholars referred to the 4th industrial revolution in the service industries' domain, we qualitatively analysed all the full texts of the documents retrieved with the Natural Language ToolKit (NLTK library) provided in Python. More specifically, we first discovered all the sentences containing references to services, and secondly, we deepened our analysis to further investigate if and how Industry 4.0 scholars examined the service industries.

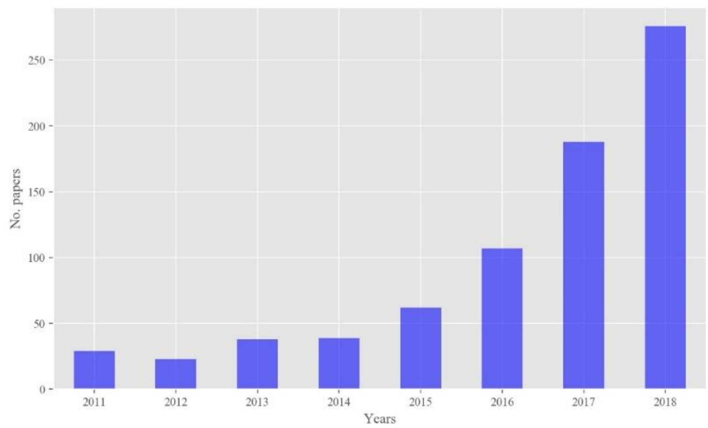
2.4. Findings

The findings depict a precise structure of the themes and technologies studied in the last few years in the managerial and social sciences research domain related to the Industry 4.0 phenomenon. Firstly, we describe the sample of collected documents from the online database, providing an overview of the material retrieved. Secondly, we present the findings obtained through the use of the bibliographical coupling technique, highlighting the main streams of literature and analysing each community detected inside the whole network. Thirdly, we propose a comprehensive framework that embeds the findings stemming from the network analysis. Finally, we analyse in-depth the role of services through the lenses of the Industry 4.0.

2.4.1 Sample Description

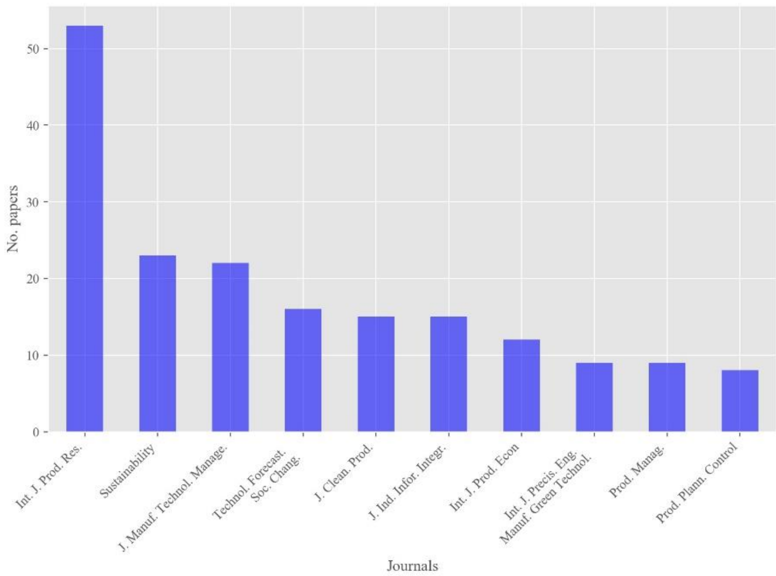
Industry 4.0 is a novel topic that has captured the curiosity and interest of management scholars in the last few years. As depicted in **Figure 6**, the trend of managerial research related to the topic increased exponentially after 2015.

Figure 6. *Publication Trend over time*



Clearly, as illustrated in **Figure 7**, in the managerial domain the most prominent journals are related to “production” and “manufacturing”. Indeed, “manufacturing” is the most used keyword, it appeared in 27% of the sampled documents. However, in the journal ranking we can find other sources, such as the “Journal of Manufacturing technology Management”, “Sustainability” and “Technological Forecasting and Social Change” which are keener to take into account the managerial and social impact of the phenomenon. Despite having chosen four main subject areas, the publications retrieved from the online database are not solely related to this restricted set. This is due to the fact that a document can belong to more than one research area. Indeed, it is interesting to notice how “engineering” and “computer science” are still associated to 20% and 10% of the retrieved papers, respectively. Thus, scholars contributing to publications in a more technical field seem also to be keen to explore the managerial impact of the new technological phenomenon.

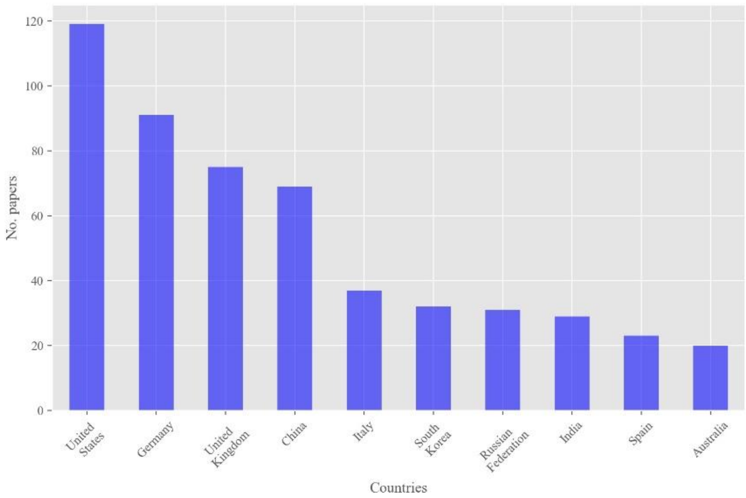
Figure 7. *Top ten journals per number of publications*



Considering the number of citations as the measure of importance of a study within the academic community, the most cited document in our sample is the work of Berman (2012) with 512 citations. In this study, the author examines in-depth the characteristics of 3-D Printing, a technology depicted as the game-changer in the new industrial revolution. Other contributions with more than 100 citations are the ones of Lee and Lee (2015), Zhong et al. (2015), Kang et al. (2016) and Ford and Despeisse (2016). As far as the authors are concerned, during the analysed time window (January 2011 - October 2018) the most active ones had at maximum of four publications: Kai-Ingo Voigt from Friedrich-Alexander-University Erlangen-Nürnberg (Germany), Morteza Ghobakhloo from University of Hormozgan (Iran) and Fei Tao from Beihang University (China).

Taking a step further, we analysed the ranking of the top 10 countries per number of affiliations (see **Figure 8**). On top, we found “United States” and “Germany”, the first two countries which announced a governmental plan aimed at boosting the introduction of Industry 4.0 technologies in manufacturing companies. The picture is completed by all other countries which have followed Germany and United States steps in this digital transformation path. The overall trend is not surprising, however, it differs in a significative way from the trend highlighted by Liao et al. (2017) which shows Germany on top of the ranking with a significative margin over all the other countries. The authors depicted an overall view of Industry 4.0 with no limitations related to the subject areas. As such, the abovementioned difference can be explained by the fact that Germany is very focused on the technical side of technological innovation, while the landscape in the managerial literature is vaster and heterogeneous and has attracted different institutions distributed all over the world.

Figure 8. *Top 10 countries per number of affiliations*



Looking more in detail at the reference list, the most cited work, with 43 citations, is the report provided by the Industrie 4.0 Working Group (Kagermann et al., 2013) which triggered the innovation wave. In second place, with 33 citations, we found the article of Lee et al. (2015) which proposed a CPS architecture for manufacturing systems in the Industry 4.0 era. Finally, with 31 citations, in third place, there is the conference paper of Hermann et al. (2016) who introduced Industry 4.0 design principles (the rank, with further details, of the 20 most referred papers is available in the **Appendix 1**).

2.4.2 Bibliographic coupling results

One of the aims of this manuscript is to provide a clear and comprehensible picture of the intellectual structure emerging from Industry 4.0 in the managerial literature. To ensure objective and reproducible results we adopted a systematic literature review methodology (Tranfield et al., 2003) using a bibliometric technique, namely bibliographical coupling, with a strong explanatory power for mapping emerging research fronts (Zupic and Čater, 2015).

In order to obtain a complete yet parsimonious set of results, we applied bibliographical coupling using different coupling thresholds on our initial set of collected documents (Mura et al., 2018). **Figures 9, 10, 11** and **12** depict the selection and refinement processes carried out, representing the bibliographical network and the communities found using different coupling thresholds. In particular, **Figure 9** shows the bibliographical network obtained embedding all the retrieved documents, while **Figure 10** depicts the findings using a coupling threshold of 4 to infer similarity embedding all the edges stemming from documents with at least a connection of weight 4. **Figures 11** and **12** represent the set of documents obtained using a coupling threshold of 8, including all the ties and just the strong ties respectively. In synthesis, the overall structure of the network is preserved using different coupling thresholds. Yet, we chose a coupling threshold of 8 to represent the main components of each community. Thus, to imply similarity between two documents, 8 shared references were needed. The network obtained as result, whose creation process has been detailed in the methodological section (see **Section 2.3.2**), was initially made of 126 edges and 99 nodes belonging to 20 different communities. However, having assessed the content of each community we decided to remove those containing just two nodes. These partitions of the network, in many cases, contained two manuscripts wrote by the same authors that can be considered as noise inside the network itself (Zupic and Čater, 2015). Hence, we ended up with a final network (visible in **Figure 12**) which includes 73 nodes and 113 edges, divided in 7 communities by the Louvain algorithm with a density of 0.043, an average degree of 3.1 and a clustering coefficient of 0.331. **Figure 12** illustrates the skeleton of the network found during the analysis, where the nodes identify papers, and an edge connects similar papers based on their shared references. The size of each node varies proportionally based to its degree (number of links), whilst the colour reveals the belonging cluster. Furthermore, inside the node is contained the paper ID (linked to the paper during the analysis phase), whose associated document is outlined in the findings section, allowing the reader to have a full comprehension of the network structure.

As clearly depicted in **Figure 12**, there are three distinctive main areas in the network: the first one includes communities 1 and 2; the second one encompasses communities 3, 4 and 5; and the last one consists of communities 6 and 7. Despite the three main components seem actually totally disconnected among each other, there are some weak linkages among them (connection with a weight less than the chosen threshold of 8, see **Figure 11**). Moreover, there are some documents that belong to a specific cluster but share some edges with nodes in other communities. This is due to the fact that some retrieved studies appear to treat both the themes of the two communities. For example, this is the case of Müller et al. (2018a), at the border of communities 1 and 2, who in the first part of the paper conducted a brief literature review on the term Industry 4.0 with the aim to find an appropriate definition for their study, topic close to the community 1. However, the main purpose of the manuscript is to assess the potential impact of Industry 4.0 technologies on business model innovation, theme that places the study closer to the topic of the community 2.

Having this network structure in mind, the next sections examine in-depth each of the seven communities extracted by the Louvain algorithm in order to understand their internal composition and assess the topics explored within them.

Figure 9. *Whole bibliographic network with all the papers sharing at least a connection with one of the retrieved papers*

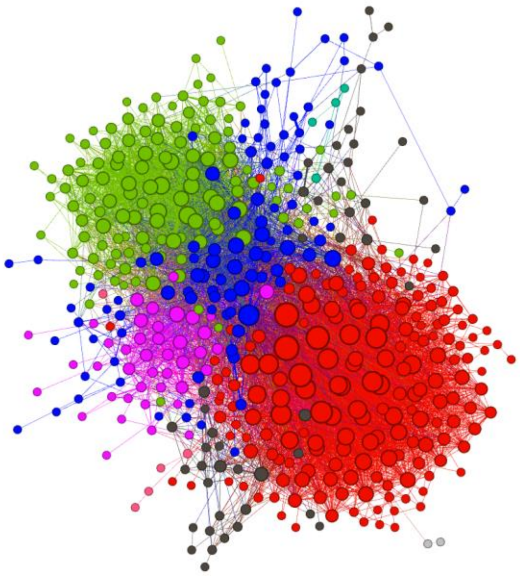


Figure 10. *Bibliographic network with coupling threshold (tie strength) equal to 4 embedding all the papers with at least an edge of weight 4 and all their ties*

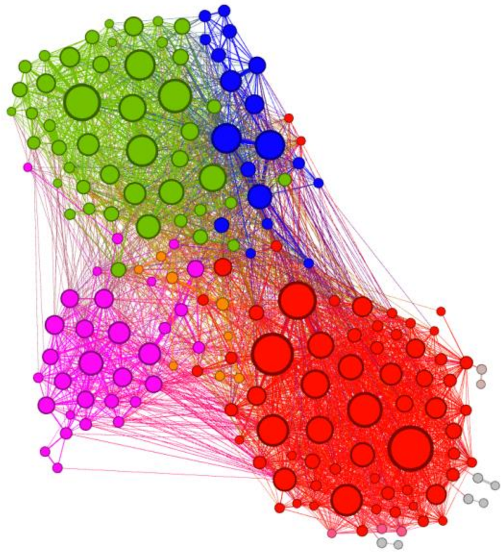


Figure 11. *Bibliographic network with coupling threshold (tie strength) equal to 8 embedding all the papers with at least an edge of weight 8 and all their ties*

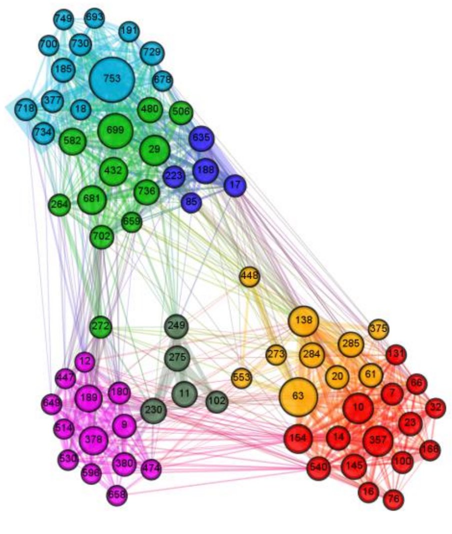
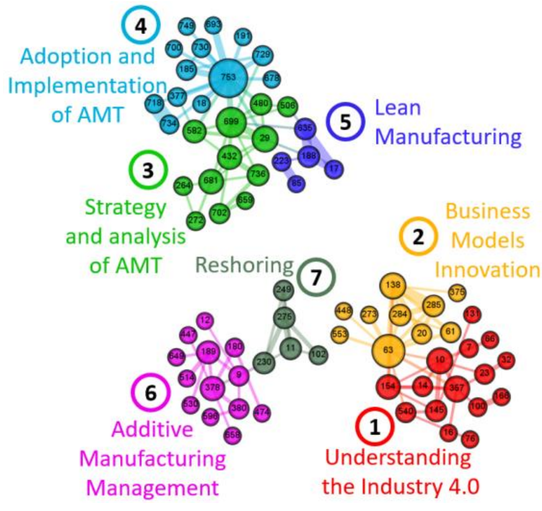


Figure 12. *Bibliographic network with coupling threshold (tie strength) equal to 8 embedding all the papers with at least an edge of weight 8 and just their strong ties (edges with weight equal or higher than 8)*



Source: authors' own elaboration

2.4.2.1 Community 1: Understanding the Industry 4.0 Phenomenon

Table 2. *Community 1 documents*

Index	Authors	Title	Year	Source title
7	Lopes de Sousa Jabbour A.B., Jabbour C.J.C., Godinho Filho M., Roubaud D.	Industry 4.0 and the circular economy: a proposed research agenda and original roadmap for sustainable operations	2018	Annals of Operations Research
10	Ghobakhloo M.	The future of manufacturing industry: a strategic roadmap toward Industry 4.0	2018	Journal of Manufacturing Technology Management
14	Dalenogare L.S., Benitez G.B., Ayala N.F., Frank A.G.	The expected contribution of Industry 4.0 technologies for industrial performance	2018	International Journal of Production Economics
16	Li L.	China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0"	2018	Technological Forecasting and Social Change
23	Tsai W.-H., Lu Y.-H.	A framework of production planning and control with carbon tax under industry 4.0	2018	Sustainability (Switzerland)
32	Tsai W.-H., Lai S.-Y.	Green production planning and control model with ABC under industry 4.0 for the paper industry	2018	Sustainability (Switzerland)
66	de Sousa Jabbour A.B.L., Jabbour C.J.C., Foropon C., Filho M.G.	When titans meet – Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors	2018	Technological Forecasting and Social Change
76	Cheng J., Chen W., Tao F., Lin C.-L.	Industrial IoT in 5G environment towards smart manufacturing	2018	Journal of Industrial Information Integration
100	Cozmiuc D., Petrisor I.	Industrie 4.0 by siemens: Steps made today	2018	Journal of Cases on Information Technology
131	Moeuf A., Pellerin R., Lamouri S., Tamayo-Giraldo S., Barbaray R.	The industrial management of SMEs in the era of Industry 4.0	2018	International Journal of Production Research
145	Wang X., Ong S.K., Nee A.Y.C.	A comprehensive survey of ubiquitous manufacturing research	2018	International Journal of Production Research
154	Bibby L., Dehe B.	Defining and assessing industry 4.0 maturity levels–case of the defence sector	2018	Production Planning and Control
166	Cozmiuc D., Petrisor I.	Industrie 4.0 by siemens: Steps made next	2018	Journal of Cases on Information Technology
357	Lu Y.	Industry 4.0: A survey on technologies, applications and open research issues	2017	Journal of Industrial Information Integration
540	Kang H.S., Lee J.Y., Choi S., Kim H., Park J.H., Son J.Y., Kim B.H., Noh S.D.	Smart manufacturing: Past research, present findings, and future directions	2016	International Journal of Precision Engineering and Manufacturing - Green Technology

This community is the core one related to the topic of Industry 4.0, and we labelled it as *"Understanding Industry 4.0 Phenomenon"* (see **Table 2**). Scholars are still looking to gain a deep understanding of the concept of Industry 4.0 and its application in different fields. Starting at a higher granularity level, Lu (2017) provides a survey of the Industry 4.0, whereas Cozmiuc and Petrisor (2018a, 2018b) analyse how Siemens is making sense of Industrie 4.0 as a model for digital disruption, identifying the state of the art and possible future steps. Moreover, Dalenogare et al. (2018) try to understand which of the set of Industry 4.0 technologies are actually expected to provide more benefits to the company, while Ghobakhloo (2018) depicts a strategic roadmap to face the advent of Industry 4.0. In particular, as highlighted by Moeuf et al. (2018), Small and Medium Enterprises (SMEs) seem not to have invested heavily in the revolution, but only in low-cost technologies related to it, such as IoT and cloud computing. Comparing Industry 4.0 with the initiative "Made in China 2025", Li (2018) focusing on emerging economies, such as China, investigates the relationship between socioeconomic changes and technological entrepreneurship. This visionary strategical plan which embeds manifold similarities with Industry 4.0, is even more challenging for nations that are not major players in the high-tech environment. Nonetheless, with the aim of excelling and progressing in their technological entrepreneurship activities, either emerging economies or developed nations can profit of the case of China and use it as a reference point.

Linking Industry 4.0 with the phenomenon of the circular economy, Jabbour et al. (2018a) show how different Industry 4.0 technologies can underpin circular economy strategies. Subsequently, Jabbour et al. (2018b) assess the possible synergies between Industry 4.0 and environmentally sustainable manufacturing. On a more granular level, on the one hand, Kang et al. (2016) provide a literature review on the concept of smart manufacturing highlighting the main structure of the phenomenon, its core technologies, and avenues for future research. As clearly stated by the authors, the term smart manufacturing is used as a synonym for the 4^{th} industrial revolution in manufacturing. On the other hand, Wang et al. (2018) delve deeper into the context of ubiquitous manufacturing research producing a comprehensive survey on the topic, that is recognised as a realizable target for the Industry 4.0 vision. Embedding the Industry 4.0 tools and principles into a specific industry, Tsai and Lu (2018) construct a green production planning and control model for the paper industry; Tsai and Lai (2018) also propose the same model for the tyre industry, whose features are different from the paper industry. At a company level, Bibby and Dehe (2018) develop a model to assess the maturity level of the Industry 4.0 phenomenon inside firms using three specific dimensions, namely people and culture, strategy, and factory of the future.

This cluster of papers highlights the fact that the complexity related to the Industry 4.0 phenomenon lacks comprehension among practitioners and scholars. Nonetheless, the latter are making the first steps toward a fuller understanding of it (Ghobakhloo, 2018; Lu, 2017; Moeuf et al., 2018) trying to discern its impact on different industries (Tsai and Lai, 2018; Tsai and Lu, 2018) and identifying its possible synergies with other economic phenomena (Jabbour et al., 2018a; Jabbour et al., 2018b).

2.4.2.2 Community 2: Business Model Innovation

Table 3. *Community 2 documents*

Index	Authors	Title	Year	Source title
20	Nagy J., Oláh J., Erdei E., Máté D., Popp J.	The role and impact of industry 4.0 and the internet of things on the business strategy of the value chain-the case of Hungary	2018	Sustainability (Switzerland)
61	Schneider P.	Managerial challenges of Industry 4.0: an empirically backed research agenda for a nascent field	2018	Review of Managerial Science
63	Müller J.M., Buliga O., Voigt K.-I.	Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0	2018	Technological Forecasting and Social Change
138	Müller J.M., Kiel D., Voigt K.-I.	What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability	2018	Sustainability (Switzerland)
273	Brooks C., Gherhes C., Vorley T., Williams N.	The nature of publicly funded innovation and implications for regional growth: Reflections from the Sheffield City Region	2018	Competitiveness Review
284	Kiel D., Arnold C., Voigt K.-I.	The influence of the Industrial Internet of Things on business models of established manufacturing companies – A business level perspective	2017	Technovation
285	Kiel D., Müller J.M., Arnold C., Voigt K.-I.	Sustainable industrial value creation: Benefits and challenges of industry 4.0	2017	International Journal of Innovation Management
375	Beier G., Niehoff S., Ziems T., Xue B.	Sustainability aspects of a digitalized industry – A comparative study from China and Germany	2017	International Journal of Precision Engineering and Manufacturing - Green Technology
448	Yang M., Evans S., Vladimirova D., Rana P.	Value uncaptured perspective for sustainable business model innovation	2017	Journal of Cleaner Production
553	Rayna T., Striukova L.	From rapid prototyping to home fabrication: How 3D printing is changing business model innovation	2016	Technological Forecasting and Social Change

The papers in this community have been classified with the theme *"Business Model Innovation"* in the context of Industry 4.0 (see **Table 3**). Indeed, technological evolution can be a pitfall for many businesses that have not developed an adequate business model (Rayna and Striukova, 2016). The main topic addressed by the documents in this community is how Industry 4.0 (Kiel et al., 2017a; Kiel et al., 2017b; Müller et al., 2018a; Nagy et al., 2018) or one of its core technologies (Rayna and Striukova, 2016; Yang et al., 2017), impacts on the business model innovation. Moreover, some studies emphasise the sustainability aspects of the implementation of the Industry 4.0 ecosystem (Kiel et al., 2017b; Müller et al., 2018b; Yang et al., 2017), a topic that overlaps between communities 1 and 2, and apparently is the facet that links them together.

Despite the economic discussion still in its infancy, all the authors in this cluster agree that Industry 4.0 technologies and design principles can fundamentally disrupt any element of traditional manufacturing business models. In particular, Kiel et al. (2017a) discover that the value proposition, internal infrastructure management, and customer relationships are the three main dimensions of the business model that are affected by undertaking Industry 4.0 initiatives. Being aware of the industrial value creation brought by Industry 4.0, Müller et al. (2018b) identify strategic, operational, as well as environmental, and social opportunities as positive drivers towards the implementation of Industry 4.0 solutions. Looking at the value creation from a sustainable angle, Kiel et al. (2017b) use the triple bottom line framework to capture the benefits and challenges of each dimension of the framework as an implication of adopting Industry 4.0. They included three more aspects to their initial framework, such as data and information, technical integration, and public context, since these are critical dimensions to qualify the Industrial Internet for effective sustainable value creation.

Going beyond the core components of the business model, Yang et al. (2017) propose an innovative perspective to pursue sustainable business model innovation, looking at the dimension of "value uncaptured". As far as technology is concerned, the one that can have the most disruptive impact on business model innovation is 3-D printing. In fact, Rayna and Striukova (2016) leveraging on the HASBRO case study, suggest the fascinating idea of using this technology for rapid prototyping, not of objects, like it was in the past, but rather of business models. This will provide companies with the capability to promptly try and test ideas. Finally, in his managerial systematic literature review, Schneider (2018) identifies the business model as one of the prominent clusters of managerial challenges in the Industry 4.0 landscape.

2.4.2.3 Community 3: Strategy and Analysis of AMT

Table 4. *Community 3 documents*

Index	Authors	Title	Year	Source title
29	Cheng Y., Matthiesen R., Farooq S., Johansen J., Hu H., Ma L.	The evolution of investment patterns on advanced manufacturing technology (AMT) in manufacturing operations: A longitudinal analysis	2018	International Journal of Production Economics
264	Mishra R., Pundir A.K., Ganapathy L.	Empirical assessment of factors influencing potential of manufacturing flexibility in organization	2018	Business Process Management Journal
272	Eyers D.R., Potter A.T., Gosling J., Naim M.M.	The flexibility of industrial additive manufacturing systems	2018	International Journal of Operations and Production Management
432	Narkhede B.E.	Advance manufacturing strategy and firm performance: An empirical study in a developing environment of small- and medium-sized firms	2017	Benchmarking
480	Kong T., Feng T., Ye C.	Advanced manufacturing technologies and green innovation: The role of internal environmental collaboration	2016	Sustainability (Switzerland)
506	Moyano-Fuentes J., Sacristán-Díaz M., Garrido-Vega P.	Improving supply chain responsiveness through Advanced Manufacturing Technology: the mediating role of internal and external integration	2016	Production Planning and Control
582	Bello Pintado A., Kaufmann R., Merino Diaz-de-Cerio J.	Advanced manufacturing technologies, quality management practices, and manufacturing performance in the southern cone of Latin America	2015	Management Research
659	Thomé A.M.T., Sousa R.S., Do Carmo L.F.R.R.S.	Complexity as contingency in sales and operations planning	2014	Industrial Management and Data Systems
681	Kim M., Suresh N.C., Kocabasoglu-Hillmer C.	An impact of manufacturing flexibility and technological dimensions of manufacturing strategy on improving supply chain responsiveness: Business environment perspective	2013	International Journal of Production Research
699	Bülbül H., Ömürbek N., Paksoy T., Bektaş T.	An empirical investigation of advanced manufacturing technology investment patterns: Evidence from a developing country	2013	Journal of Engineering and Technology Management - JET-M
702	Helkiö P., Tenhiälä A.	A contingency theoretical perspective to the product-process matrix	2013	International Journal of Operations and Production Management
736	Liu N., Roth A.V., Rabinovich E.	Antecedents and consequences of combinative competitive capabilities in manufacturing	2011	International Journal of Operations and Production Management

This cluster has been labelled as *"Strategy and analysis of advanced manufacturing technologies (AMT)"* (see **Table 4**). The scholars here try to analyse the various impacts that AMT can have on the firm. With AMT they refer to a concept wide known in manufacturing strategic literature (see Boyer and Pagell, 2000) which has been introduced with the advent of the computer inside the company. However, the relationships and concepts analysed in this group of documents, as in the case of Cheng et al. (2018), will become even more important with the introduction of Industry 4.0 technologies. Looking in more detail at the community, Eyers et al. (2018) and Mishra et al. (2018) find a positive impact of AMT on flexibility dimensions of the company, while Kim et al. (2013) combining them investigate the impact of the last two factors on manufacturing strategies on improving supply chain responsiveness. Using an empirical study, Narkhede (2017) examines the link between a business strategy that uses AMT and firm performance. On the same stream of research, Bello-Pintado et al. (2015) focus on quality management practices related to AMT. Referring to the investment strategies, Bülbül et al. (2013) and Cheng et al. (2018) assess the dynamic nature of investments pattern in AMT. The strategy needs to acknowledge the fit of the investment with the overall objectives of the company (Cheng et al., 2018). Besides, despite different investment patterns can be found, they seem to be not significantly correlated with firm performance or ownership (Bülbül et al., 2013). Finally, Liu et al. (2011), considering a cumulative model, discover a positive relationship between AMT and business unit's combinative competitive capabilities.

2.4.2.4 Community 4: Adoption and implementation of AMT

Table 5. *Community 4 documents*

Index	Authors	Title	Year	Source title
18	Altuntas S., Cinar O., Kaynak S.	Relationships among advanced manufacturing technology, innovation, export, and firm performance: Empirical evidence from Turkish manufacturing companies	2018	Kybernetes
185	Kumar R., Singh H., Chandel R.	Exploring the key success factors of advanced manufacturing technology implementation in Indian manufacturing industry	2018	Journal of Manufacturing Technology Management
191	Bhandari D., Singh R.K., Garg S.K.	Justification of advanced manufacturing technologies for small and medium enterprises from auto component sector: AHP approach	2018	International Journal of Productivity and Quality Management
377	Borges L.A., Tan K.H.	Incorporating human factors into the AAMT selection: a framework and process	2017	International Journal of Production Research
678	Lewis M., Åhlström P., Yalabik B., Mårtensson P.	Implementing advanced service technology in the public sector: An exploratory study of the relevance and limitations of insights from private sector manufacturing technology implementation	2013	Production Planning and Control
693	Singh H., Kumar R.	Hybrid methodology for measuring the utilization of advanced manufacturing technologies using AHP and TOPSIS	2013	Benchmarking
700	Goyal S., Grover S.	A fuzzy multi attribute decision making approach for evaluating effectiveness of advanced manufacturing technology - in Indian context	2013	International Journal of Productivity and Quality Management
718	Scannell T.V., Calantone R.J., Melnyk S.A.	Shop floor manufacturing technology adoption decisions: An application of the theory of planned behavior	2012	Journal of Manufacturing Technology Management
729	Darbanho-sseiniamirkhiz M., Wan Ismail W.K.	Advanced manufacturing technology adoption in SMEs: An integrative model	2012	Journal of Technology Management and Innovation
730	Saberi S., Yusuff R.M.	An exploratory study into advanced manufacturing technology (AMT) usage in Malaysian small- and medium-sized enterprises (SMEs)	2012	International Journal of Innovation and Technology Management
734	Scannell T.V., Melnyk S.A., Calantone R.J.	Shop floor manufacturing technology adoption: An adaptation of the technology acceptance model	2011	International Journal of Manufacturing Technology and Management
749	Taha Z., Banakar Z., Tahriri F.	Analytical hierarchy process for the selection of advanced manufacturing technology in an aircraft industry	2011	International Journal of Applied Decision Sciences
753	Singh H., Khamba J.S.	Utilisation of new technologies: A state-of-art-review and future prospective	2011	International Journal of Services and Operations Management

In this community, the prominent theme is the *"Adoption and implementation of AMT"* inside the company boundaries (see **Table 5**). Firstly, Singh and Khamba (2011) provide an overview of the utilisation of new technologies inside the company. This is the hub of the cluster analysed. More specifically, some papers provide a theoretical model towards adoption (Borges and Tan, 2017; Darbanhosseiniamirkhiz and Wan Ismail, 2012; Scannell et al., 2011) while others suggest a methodology to measure the effective degree of utilization of AMT (Goyal and Grover, 2013). Considering only SMEs, on one hand, Saberi and Yusuff (2012) claim that technology does not play a critical role in its users; on the other hand, later in time, Bhandari et al. (2018) argue that only a judicious application of AMT can improve SMEs' performance. In their singular case study, Lewis et al. (2013), use an AMT model to assess a project in the service sector. Using top management support, technological-organisational adaption, and training people as main elements of their model, they find many similarities but also some differences.

2.4.2.5 Community 5: Lean Manufacturing Implementation

Table 6. *Community 5 documents*

Index	Authors	Title	Year	Source title
17	Ghobakhloo M., Azar A., Fathi M.	Lean-green manufacturing: the enabling role of information technology resource	2018	Kybernetes
85	Ismail K., Isa C.R., Mia L.	Market competition, lean manufacturing practices and the role of Management Accounting Systems (MAS) information	2018	Jurnal Pengurusan
188	Ghobakhloo M., Azar A.	Business excellence via advanced manufacturing technology and lean-agile manufacturing	2018	Journal of Manufacturing Technology Management
223	Ismail K., Isa C.R., Mia L.	Evidence on the usefulness of management accounting systems in integrated manufacturing environment	2018	Pacific Accounting Review
635	Ghobakhloo M., Hong T.S.	IT investments and business performance improvement: The mediating role of lean manufacturing implementation	2014	International Journal of Production Research

Each document on this group focuses on a specific advanced manufacturing technique, the *"Lean manufacturing (LM)"* paradigm (see **Table 6**). The latter is defined as the process of "*systematic elimination of wastes from an organisation's operations through a set of synergistic work practices to produce products and services at the rate of demand*" (Ghobakhloo and Hong, 2014: p. 5367). This is one of the possible strategies that can guide manufacturing companies to attain the desired outcomes and sustaining their competitiveness over time. In particular, scholars in this cluster evaluate the link between information technologies (IT), AMT, and the effective implementation of LM. Using a questionnaire-based survey, Ghobakhloo and Hong (2014) find that LM and IT are mutually interdependent, and an investment in IT can lead to business performance improvement through enhancing the level of LM implementation. A critical role for a successful implementation process is played by AMT competency (Ghobakhloo and Hong, 2014). However, later in time, IT competencies in LM have been found to be just as a lower-order organisational capability (Ghobakhloo et al., 2018). Indeed, since environmental practices are the main benefit of LM implementation, the business value provided by IT competencies needs to be assessed in terms of LM effectiveness and environmental management capabilities (Ghobakhloo et al., 2018). On the same stream of research, Ghobakhloo and Azar (2018) argue that AMT has a significant impact on the development of not just LM, but also agile manufacturing, as an advanced form of LM. However, LM positively contributes to operational performance, while agile manufacturing significantly impacts on marketing and financial performance. Looking more in detail at the performance, Ismail et al. (2018a) claim that the use of management accounting systems has a positive impact on the use of integrated manufacturing practices, which in turn is positively associated with the performance. Besides, Ismail et al. (2018b) find that the same type of systems has even a positive mediating role on market competition, LM, and organisational performance.

2.4.2.6 Community 6: Additive Manufacturing Management

Table 7. *Community 6 documents*

Index	Authors	Title	Year	Source title
9	Chekurov S., Metsä-Kortelainen S., Salmi M., Roda I., Jussila A.	The perceived value of additively manufactured digital spare parts in industry: An empirical investigation	2018	International Journal of Production Economics
12	Martinsuo M., Luomaranta T.	Adopting additive manufacturing in SMEs: exploring the challenges and solutions	2018	Journal of Manufacturing Technology Management
180	Murmura F., Bravi L.	Additive manufacturing in the wood-furniture sector: Sustainability of the technology, benefits and limitations of adoption	2018	Journal of Manufacturing Technology Management
189	Holmström J., Liotta G., Chaudhuri A.	Sustainability outcomes through direct digital manufacturing-based operational practices: A design theory approach	2018	Journal of Cleaner Production
378	Khorram Niaki M., Nonino F.	Additive manufacturing management: a review and future research agenda	2017	International Journal of Production Research
380	Li Y., Jia G., Cheng Y., Hu Y.	Additive manufacturing technology in spare parts supply chain: a comparative study	2017	International Journal of Production Research
447	Deradjat D., Minshall T.	Implementation of rapid manufacturing for mass customisation	2017	Journal of Manufacturing Technology Management
474	Ford S., Despeisse M.	Additive manufacturing and sustainability: an exploratory study of the advantages and challenges	2016	Journal of Cleaner Production
514	Holmström J., Holweg M., Khajavi S.H., Partanen J.	The direct digital manufacturing (r)evolution: definition of a research agenda	2016	Operations Management Research
530	Sasson A., Johnson J.C.	The 3D printing order: variability, supercenters and supply chain reconfigurations	2016	International Journal of Physical Distribution and Logistics Management
596	Chen D., Heyer S., Ibbotson S., Salonitis K., Steingrímsson J.G., Thiede S.	Direct digital manufacturing: Definition, evolution, and sustainability implications	2015	Journal of Cleaner Production
649	Holmström J., Partanen J.	Digital manufacturing-driven transformations of service supply chains for complex products	2014	Supply Chain Management
658	Yoon H.-S., Lee J.-Y., Kim H.-S., Kim M.-S., Kim E.-S., Shin Y.-J., Chu W.-S., Ahn S.-H.	A comparison of energy consumption in bulk forming, subtractive, and additive processes: Review and case study	2014	International Journal of Precision Engineering and Manufacturing - Green Technology

This group is mainly related to the *"Additive Manufacturing management"* (see **Table 7**). In fact, the documents analyse different faces related to the adoption of direct digital manufacturing at a firm level (see Chen et al., 2015 for a definition). Interestingly, additive manufacturing management is part of a recent and unexplored research line (Khorram Niaki and Nonino, 2017). As such, works on this cluster, on the one hand, propose a research agenda towards the managerial implications of the phenomenon (Chen et al., 2015; Holmström et al., 2018; Khorram Niaki and Nonino, 2017), and on the other hand, conduct exploratory studies on the practical investigation of the direct digital manufacturing applications at a firm level (Chekurov et al., 2018; Li et al., 2017; Martinsuo and Luomaranta, 2018; Murmura and Bravi, 2018). The stream of managerial research of this group tries to understand the potential of the introduction of additive manufacturing techniques inside the company and the main concern is about the sustainability that the adoption of this concept can bring in terms of the sources of innovation and the configuration of value chains (Deradjat and Minshall, 2017; Ford and Despeisse, 2016; Holmström et al., 2016; Murmura and Bravi, 2018; Sasson and Johnson, 2016). In essence, this community leverages on the argument that 3-D printing will be the pivotal driver in the new industrial revolution (Berman, 2012).

2.4.2.7 Community 7: Reshoring

Table 8. *Community 8 documents*

Index	Authors	Title	Year	Source title
11	Moore M.E., Rothenberg L., Moser H.	Contingency factors and reshoring drivers in the textile and apparel industry	2018	Journal of Manufacturing Technology Management
102	Ancarani A., Di Mauro C.	Reshoring and industry 4.0: How often do they go together?	2018	IEEE Engineering Management Review
230	Moradlou H., Tate W.	Reshoring and additive manufacturing	2018	World Review of Intermodal Transportation Research
249	Nujen B.B., Halse L.L., Damm R., Gammelsæter H.	Managing reversed (global) outsourcing – the role of knowledge, technology and time	2018	Journal of Manufacturing Technology Management
275	Barbieri P., Ciabuschi F., Fratocchi L., Vignoli M.	What do we know about manufacturing reshoring?	2018	Journal of Global Operations and Strategic Sourcing

This is a very recent cluster, all the articles have been published in 2018 and they are related to the phenomenon of *"Reshoring"* (see **Table 8**). As argued by Barbieri et al. (2018: p. 79) this process refers to "*the decision to bring back to the home country production activities earlier offshored*". Following a literature review methodology, Barbieri et al. (2018) aim at understanding the phenomenon of reshoring, classifying extant literature in order to find key factors that lead companies to re-shore their production. Taking into account the technological layer, Barbieri et al. (2018) conclude prospecting a future research question related to the impact of Industry 4.0 technologies on reshoring. Trying to answer this research question empirically, Ancarani and Di Mauro (2018) fail to prove a strong relationship between technologies belonging to the Industry 4.0 domain and the willingness of reshoring based on cost reduction reason. Referring to a specific technology, Moradlou and Tate (2018) focus on additive manufacturing to seek potential beneficial areas where this technique can act as a driver of reshoring strategies for UK companies. Conducting a case study in Scandinavia, Nujen et al. (2018) shed light on the critical role played by knowledge in case of reshoring. It seems to be a challenge for the company to renew and revive capabilities to perform advanced manufacturing back home. Resources, like skilled workers, policies, and regulations need to be considered by companies in case of reshoring (Moore et al., 2018).

2.4.3 Framework discussion

With the aim of bringing all the communities together and providing a clear understanding of the big picture for the reader we created a comprehensive framework to summarize the study's findings (see **Figure 13**). A bottom-up approach will be used to describe the obtained framework. Firstly, looking more in details at the three main components of the network structure (see **Figure 12**) we used a technological layer to classify them into three distinctive categories, namely AMT (communities 3, 4 and 5), Industry 4.0 technologies (communities 1 and 2) and additive manufacturing (communities 6 and 7). They represent diverse streams of literature with some similarities among them. At the base of the framework designed, we placed the studies which investigate the impact and development of AMT which act as enabler layer for the adoption and exploration of the Industry 4.0 concept (Cheng et al., 2018). Inside the Industry 4.0 block, we embedded a layer called 3D-printing since this is the reference technique in the realm of the additive manufacturing (Rayna and Striukova, 2016), one of the core technologies of the 4th Industrial Revolution, which has gained particular attention from management scholar in the last few years (see community 6) and it is supposed to revolutionise the entire value chain (Berman, 2012).

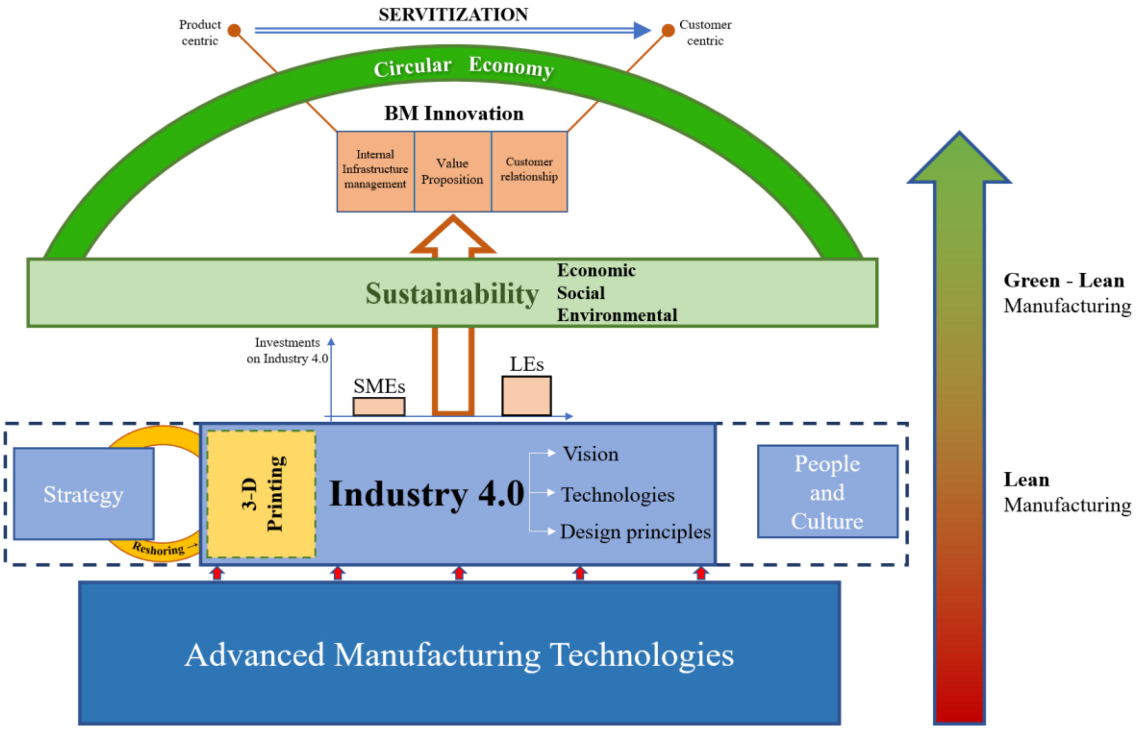
Referring to the Industry 4.0, it has been approached under different facets, trying to provide its vision (Kagermann et al., 2013), understanding its core technologies (Chiarello et al., 2018; Kang et al., 2016; Lu, 2017) and its design principles (Hermann et al., 2016). In order to understand the maturity at a firm level of the adoption of Industry 4.0 initiatives, we connected the Industry 4.0 block to other two blocks, namely "strategy" and "people and organization" as suggested by Bibby and Dehe (2018). In particular, on the left-hand side, as one of the possible strategies guided by the Industry 4.0 adoption, we introduce a reshoring component, due to the increasing literature suggesting this relationship (see community 7). Analysing the investment, as depicted by Moeuf et al. (2018) compared to large enterprises (labelled as LEs in **Figure 13**), SMEs seem not to have invested heavily in the revolution, but just on low-cost technologies related to it, such as IoT and cloud computing. In the centre of the figure, a big arrow is connecting the Industry 4.0 (community 1) and business model innovation (community 2) surpassing a sustainability layer, a concept that is presented in both the discovered communities, and it is discussed in terms of its three pillars, economic, social and environmental aspects (Kiel et al., 2017b). As suggested by Kiel et al. (2017a) the three dimensions of the business model which are mainly influenced by undertaking Industry 4.0 initiatives are the value proposition, the internal infrastructure management and the customer relationship. Concerning the sustainability theme and business model innovation, Jabbour et al. (2018a) proposed a link between the circular economy and Industry 4.0 providing insights on how to exploit Industry 4.0 technologies to pursue diverse business model innovation under the circular economy vision.

On the right-hand side, a big arrow runs through the entire framework based on the concept of lean manufacturing (see community 5) which has been linked to the introduction of AMT into the firm and also associated with the adoption of Industry 4.0 since the latter has been proved capable to implement the lean paradigm (Sanders et al., 2016). Reaching, in a figurative sense, the sustainability layer, from lean manufacturing we move to green-lean manufacturing.

As far as the top section of the framework is concerned, in order to become a full adopter of Industry 4.0 and capture all the value unleash by the phenomenon, companies seem to have to add services in their value offer (Müller et al., 2018a). Following this strategy, firms are changing their orientation from a product-centric to a customer-centric, embracing the "*servitization paradigm*" (see Neely, 2008; Vandermerwe and Rada, 1988), defined as the "*process of building revenue streams for manufacturers from services*" (Baines et al., 2017: p. 257), and moving from passive adopters to providers of Industry 4.0 solutions (Müller et al., 2018a).

The theme of services will be analysed in-depth in the next section, which will also highlight them as a promising future component of the 4th industrial revolution either in the manufacturing industries or in other industries.

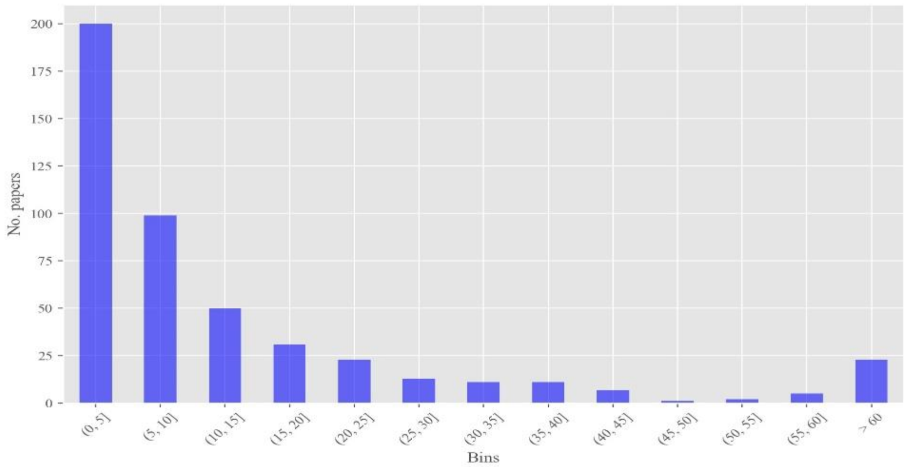
Figure 13. *Conceptual Framework Industry 4.0's managerial and social sciences literature (Source: authors' elaboration)*



2.4.4 Impact on services

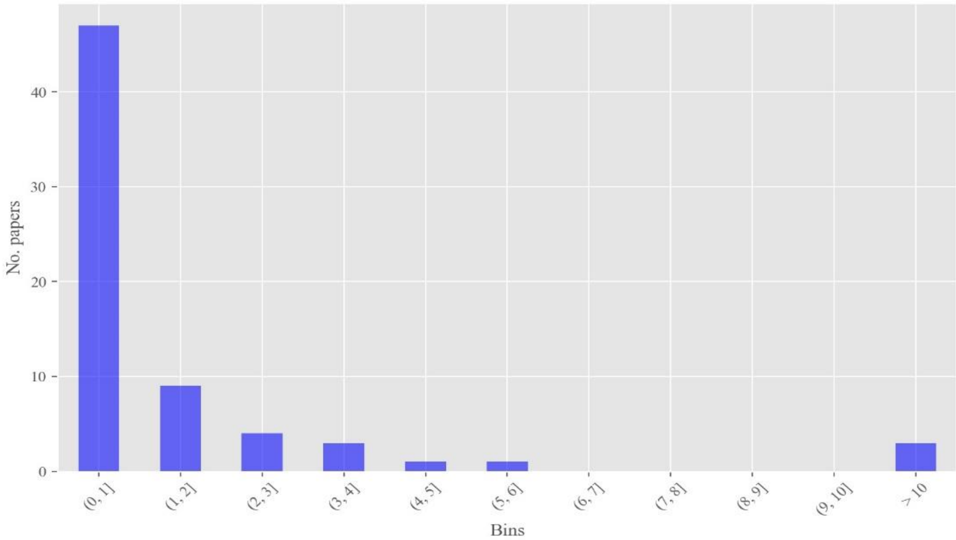
With the aim of providing an answer to the second research question, we analysed the full text of all the retrieved documents. In the first step of our analysis, we looked for keywords inside the text of the papers. At a more granular level, we conducted a preliminary analysis of the keyword "service", counting its absolute occurrences. As shown in **Figure 14**, the distribution of the term "service" among the set of collected documents is right-skewed. Indeed, many of the studies only mentioned the concept a few times. Nevertheless, in the long tail of the distribution, where we placed a final bin for documents with over 60 occurrences, there seemed to be several documents that constantly deploy the keyword "service".

Figure 14. *Distribution of the term "service" among set of collected documents.*



To validate these first insights, we looked for the keywords "*service* industr**" or "*service* sector**". As depicted in **Figure 15**, despite the overall shape of the distribution remaining the same, the absolute frequencies remarkably decreased. In fact, 47 documents introduced the concepts one time and just 21 more than once. Having the results of this analysis in mind, we took a further step analysing the sentences related to services in the set of collected studies, trying to capture their link with the Industry 4.0 phenomenon.

Figure 15. *Distribution of "service* sector*" or "service* industry*" among the set of collected studies.*



Among all the analysed studies, the very first attempt to bridge Industry 4.0 and servitization has been made by Lee at al. (2014) who design a CPS framework for self-aware and self-maintenance machines, exploiting Industry 4.0 technologies for service innovation and smart analytics. The authors stated that exploiting the CPS framework in service innovation will lead companies to properly benefit from the information hidden in the Industrial Big Data environment, arguing that service innovation is one of the inevitable trends and challenges for manufacturing industries adopting the Industry 4.0 vision. However, the framework and case study proposed by the authors result rooted in engineering literature, and more useful to tackle the technical side of the phenomenon under investigation.

From a business strategy perspective, the first movers were Kans and Ingwald (2016) who coined the term Service Management 4.0 where the focus of a company is in delivering value to the customer through their value offer. In particular, this new concept embeds four key aspects: performance-based contracts, the business ecology concept, partnering, and the mix of products and services in customer offers. The authors' conceptual framework clearly shows four levels of business development as logical steps a company undertakes to shift its focus from product to solution (bundle of products and services) provider (fourth level). This last layer, from the authors' perspective, is the one which supports Industry 4.0 from an industrial development point of view and refers to Service Management 4.0. Nonetheless, despite the framework can help companies understand their current business model, the phases of the transformation process are not accurately linked together and since it is a conceptual framework, no empirical evidence are provided to test its assumptions.

A year later, adopting a multiple case study approach, Arnold et al. (2016) and Kiel et al. (2017a) provided qualitative empirical evidence to confirm the findings of Kans and Ingwald (2016). The authors claim that for large companies, undertaking Industry 4.0 projects, a consequent service orientation is of crucial importance in association with a more customer-centric view and an intensification of the customer relationships and extended customer-oriented communication aiming at a complete comprehension of customers' needs. Indeed, a wide range of companies in their samples is changing the value proposition of their business models towards a bundle of products and services. In this data-driven servitization environment, the customer becomes a collaborative partner that needs to be integrated into the service and product design and engineering (Arnold et al., 2016). Since the Industrial IoT largely facilitates customization, Kiel et al. (2017a) argue that the natural consequence, in an Industry 4.0 environment will be an individualized service orientation. Therefore, companies should always be ready to innovate their established business models in terms of hybrid and truly customizable product-service solutions triggered by the implementation of Industry 4.0 initiatives, using for example pay-per-use and platform based business models (Kiel et al., 2017b). Nevertheless, in both their multiple case studies, using semi-structured interviews both Arnold et al. (2016) and Kiel et al. (2017a) analysed manufacturing firms, that despite operating in different industries, were embedded in the German context and mainly having a high number of employees[1]. Thus, their findings lack generalisation for the entire landscape of manufacturing companies[2]. Indeed, as stated by Kiel et al. (2017a), their study should be extended to service providers to investigate potential discrepancies in the transition from product to solution providers, shedding lights on the intensities of the Business Model component modifications. In fact, as indicated by Bienhaus and Haddud (2018), there is still a remarkable gap between the manufacturing sector and the service sector when referring to the digital revolution and transformation.

Adopting the same methodological approach as Kiel et al. (2017a), Müller et al. (2018a) highlight the fact that pursuing a service business model innovation, adding services to the current value offer, is a worth path also for manufacturing German SMEs. The results of their study suggest that "*servitization allows new forms value capture and that companies, which introduce services in their value offers, are the ones likely to profit the most from value capture innovation through Industry 4.0*" (Müller et al., 2018a: p. 9). These findings, to a certain extent, widen the

[1] More than 80% of the samples are made by firms with more thank 1000 employees.

[2] For example, Small and Medium Enterprises account for 99% of the companies located in the EU.

literature review findings of Moeuf et al. (2018) who point out that when pursuing Industry 4.0 initiatives, SMEs seem to limit their investments to the adoption of IoT and cloud computing. These technologies, despite not precisely specified by Müller et al. (2018a) (who consider CPS as the technological driver of Industry 4.0 in their survey), may be the ones that allow companies to pursue servitization paths. It will be interesting in future studies to unpack Müller et al. (2018a)'s findings, exploring how the wider set of technologies related to the Industry 4.0 can guide companies' servitization.

If we look at studies outside the German borders, Bonfanti et al. (2018) explore the diverse set of strategic paths in digital manufacturing attempts embraced by Italian craft firms. The authors summarise their results in three distinctive directions: to take advantage of the use of new digital technologies, to expand the firm network of partners embedding the customer into the processes concerning the design and production, and to surround the product with a wider offer of services related to it. According to the authors, undertaking a strategy that embraces all three stated paths in a digital manufacturing environment will allow companies to survive and potentially increase their competitive advantage. Thus, technology, customer-centric view, and servitization can be considered as the three critical aspects of a successful implementation of Industry 4.0 projects.

This service-orientation will be guided by a specific antecedent that can be undoubtedly identified in the abundant amount of data that will be generated by this unprecedented fusion of the digital and physical domains. Simply, "*The fourth industrial revolution is based on data*" (Nagy et al., 2018: p. 2). Talking about the strategy to address the Industry 4.0 phenomenon, Müller et al. (2018b: p. 5), clearly state that: "*Data play a critical role in this context, since an increasing fusion of physical products and services with digital, data-centered enhancements and solutions is expected. A consequent orientation towards services is expected, which accelerates the vanishing separation between product manufacturing and service provision.*" Their results are in line with Yang et al. (2017), that analysing product-service systems firms using AMT, show that the dimension of value uncaptured related to the middle of life phase of the product life cycle is mainly related to service data. The availability of data, which is placed at the base of the wisdom hierarchy for scholars in information system management (Rowley, 2007), will provide the foundation for generating new knowledge. In fact, using advanced manufacturing techniques, exploiting automation, sensing and information technology provides the infrastructure to collect and store service data in real-time which, manipulated through big data analytics techniques, can potentially create massive value for the company (Mariani and Fosso Wamba, 2020; Mariani et al., 2018a; Yang et al., 2017). Yet, data itself does not provide a competitive advantage. In fact, as depicted by Porter and Heppelmann (2014), companies need to carefully decide how to create their portfolio of digital services based on their customers' preferences since their aim must be to create value for the buyer. However, as reported in the recent conceptual work of Frank et al.

(2019), at the intersection of servitization and Industry 4.0, Industry 4.0-related services should not only add value for the customers but also provide benefits for companies' internal processes. Following the authors' view, firms should leverage data to shape digital services that can be useful for both sides, thus augmenting the complexity of the business model innovation process.

Overall, our findings seem to suggest that Industry 4.0 research pertaining to service industries is still at a very embryonic stage. For example, in his recent literature review, Schneider (2018: p. 833) provides some future research challenges related to the provision of digital services: "*What digital services are actually demanded or most urgently needed? For which of these services are the customers willing to pay (and how much)?* […] *Will Industry 4.0 technologies (thus) provide the possibility to overcome the service paradox (cf., Cenamor et al., 2017)?*". Most of these interrelated questions remain unanswered in the service industries and, generally, the tertiary sector. Moreover, while some servitization scholars (Adrodegari and Saccani, 2017; Baines et al., 2017) adopted a service-dominant logic (Vargo and Lusch, 2004; 2008), so far no study has addressed how Industry 4.0 technologies can help companies and customers co-create value, with the exception of the work of Rayna and Striukova (2016). They studied HASBRO to show how additive manufacturing (3-D printing) can be used for rapid prototyping of business models rather than objects; this process can be driven by collaboration with users who would construct their own models online.

However, the studies analysed so far, despite highlighting the fact that a future orientation toward services is expected focus uniquely on the manufacturing industry. Thus, in order to expand our horizon, we examined whether Industry 4.0 technologies and design principles can encompass the manufacturing sector and be also applied to other industries. Talking about the growing research stream discussing servitization and service business model innovation, Müller et al. (2018a) highlight the study of Rennung et al. (2016) which can be considered unique in is genre. In fact, the authors, aware that despite being embedded in the first conceptualization of the Industrie 4.0 plan (Kagermann et al., 2013), services have been largely neglected by scholars investigated the phenomenon, conducted a survey on 80 well established service provider companies. In their study they administered a questionnaire regarding the effect of the Industry 4.0 characteristics on different phases of the service life cycle. From their findings the authors claimed that "*the service engineering and management can be an important component of the project "Industry 4.0"*" (Rennung et al., 2016: p. 377). Their results have been corroborated by the recent exploratory research conducted by Nagy et al. (2018) on Hungarian companies, in which part of the study sample consisted of logistic service companies. Service companies embracing the Industry 4.0 paradigm and vision were found capable of increasing market and financial performance and enhancing their competitiveness by improving the level of the services, cooperation capabilities, and business processes. This is a symptomatic clue that the Industry 4.0

framework is not circumscribed to the manufacturing industry, but it can have remarkable implications also for other industries.

Going beyond the set of retrieved documents of this study, there are some examples related to the use of cutting-edge technologies that can be associated with the technological ecosystem of the Industry 4.0 in the service industries. Indeed, services scholars have started to investigate the digital transformation of services (Rust and Huang, 2014), where the main source of innovation seems to be related to the gradual infusion of artificial intelligence in machines (Huang and Rust, 2020; Jörling et al., 2019). Remarkable examples stem from the application of service robots in the tourism and hospitality domain (Ivanov et al., 2019) since these intelligent machines having the ability to interact with the service customer (Wirtz et al., 2018) can completely redefine the service experience (Larivière et al., 2017) and especially the tourist experience (Tung and Law, 2017). For instance, YOTEL Singapore Orchard Road has recently created a holiday package entirely related to the human-robot interaction, called ROBO-CATION (YOTEL Singapore, 2020). The two service robots deployed in the hotel operations, Yoshi and Yolanda, can exchange information among them and with other digital devices, as well as transmit the data they gather to the "mission control unit" within the hotel (Singapore Business Review, 2019). This system, using an Industry 4.0 lens, can be seen as a CPS leveraging on the design principles of interconnection and technical assistance since data collected from service robots can be used to better inform strategic decision-making within the hotel. However, the most striking example of CPS, close to the concept of the smart factory in the hotel domain, is the one deployed by Henn na Hotel in Japan. The company has pushed the introduction of service robots and digital technologies to the boundaries, fully automating its hotels (see Ivanov et al., 2019). Human employees manage the entire system in the background shifting their role from operators to flexible problem solvers and strategic decision-makers, as per the smart factory vision (Hermann et al., 2016). Yet, these are just examples taken from the real world that are out of the scope of the manufacturing industries but embed part of the Industry 4.0 key concepts, design principles, and technologies. Hence, as argued by Rennung et al. (2016) the intrinsic characteristics of the Industry 4.0 go beyond the manufacturing industries, also including services. Nonetheless, services scholars have only loosely linked the digital transformation of services to the Industry 4.0 (i.e., Huang and Rust, 2020), without fully taking advantage of the progress made in the Industry 4.0 literature to inform services research.

To sum up, managerial research on Industry 4.0 has been mainly confined to the manufacturing sector. Indeed, services have been examined mainly by Industry 4.0 scholars. The latter have addressed servitization within the manufacturing industries from both an engineering (Lee et al., 2014) and managerial perspectives (Kans and Ingwald, 2016). As such, services have not been considered as an application field of Industry 4.0 technologies. Yet, embracing a servitization strategy will provide the opportunity for companies to shift from mere products supplier to become providers of Industry 4.0 solutions (Müller et al., 2018a), adopt a customer-centric perspective (Kiel et al., 2017a), and, eventually, capture the entire value created by the deployment of Industry 4.0 initiatives (Yang et al., 2017). This will increasingly blur the line between the manufacturing and service industries (Lee et al., 2014). Essentially, embedding products with digital services, in the Industry 4.0 era, will be the true source of competitive advantage (Nagy et al., 2018) since this is supposed to add value to customers and companies' internal processes at the same time (Frank et al., 2019). Nevertheless, extant studies are mainly exploratory and, even though their results can be used as a foundation for future investigations, they claim for a wider generalization using for instance large-scale samples of firms within and across industries and countries. Ultimately, this will allow innovation scholars to enrich our knowledge of the broad 4th Industrial Revolution phenomenon.

2.5 Discussion

2.5.1 Research Agenda

As highlighted by several authors in the past, research revolving around the 4th Industrial Revolution lacks proper theoretical underpinnings, presenting usually a more practical value, that makes it difficult to systematize and enhance scholarly knowledge revolving around the phenomenon (Hermann et al., 2016; Müller et al., 2018a). However, drawing on the findings of this systematic quantitative literature review we have devised the following research agenda. First, scholars in management and social sciences aiming to explore the phenomenon of the Industry 4.0 can leverage on the conceptual framework provided in this work (**see Figure 13**) to better position their investigations. Besides, they can build on the overarching framework provided to extend our conceptualization and build a joined-up body of knowledge related to the Industry 4.0. Second, based on the findings in **Section 2.4.4**, we suggest that future intellectual efforts should focus on the transition of the 4th Industrial Revolution towards services and the service industries. To this end, it would be highly important to understand through conceptual and especially empirical examinations how the Industry 4.0 design principles and related technologies can play a pivotal role in the design of services. Besides, it would be crucial to understand the interplay of Industry 4.0 and Service 4.0 initiatives, to evaluate whether manufacturing companies investing in Industry 4.0 initiatives should shift their emphasis on the enhancement of product-related services. Third, we encourage scholars to specifically focus on the antecedents and consequences of the introduction of the Industry 4.0 paradigm, technologies, and design principles within the service industries. Based on the study's results we suggest the use and combination of a precise set of theoretical underpinnings and emerging disciplinary fields, namely institutional theory, digital entrepreneurship, service-dominant logic, and digital business models. First, due to the importance of governments in promoting and shaping initiatives related to the Industry 4.0 (Reischauer, 2018), we expect that following the lead of the German

"Smart Service World" plan (German Federal Ministry, 2017), a wide range of countries will soon develop their developmental plans for the service industries. These would allow governments to play a remarkable role also in guiding the digitalization of services. Therefore, the principles related to the institutional theory (DiMaggio and Powell, 1983; Meyer and Rowan, 1977) could be helpful for researchers aiming to disentangle the underlying mechanisms that lead companies to innovate, complying with the plans devised by governmental institutions. This will reveal the role that the latter are playing in shaping the 4th Industrial Revolution. Second, another interesting theoretical lens could be the one related to digital entrepreneurship (Nambisan, 2017). Indeed, as devised by the seminal study of Nambisan (2017) new digital technologies have the power to disrupt extant entrepreneurial processes and redefine the locus of entrepreneurial agency. Yet, to the best of our knowledge, no study has tried to understand the role of digital entrepreneurs in the context of the Industry 4.0 and especially in its realisation in the service industries. Combining this approach with the highlighted technological pillars and design principles of the new industrial revolution could help scholars in the digital entrepreneurship domain to effectively capture the reasons that allow digital platforms and ecosystems to prosper and trigger innovation initiatives potentially linked to the Industry 4.0 phenomenon. As such, this will enrich scholarly knowledge in the literature at the intersection of digital technologies and entrepreneurship (Evans and Schmalensee, 2016; Parker and Van Alstyne, 2018; Nambisan, 2017; Nambisan et al., 2019). Third, transcending from the difference between products and services and complying with the vision of companies able to provide Industry 4.0 solutions (Müller et al., 2018a) a useful theoretical ground can be provided by the service-dominant logic (Vargo and Lusch, 2004; 2008) where companies have a service-centered view and can only offer value propositions to future costumers. The use of this theory will not only support scholars trying to disentangle the specificity of Industry 4.0 initiatives within the service industries but also help them make more sense of the servitization phenomenon that is increasingly blurring the line between manufacturing and service industries. In particular, since value is always co-created following the service-dominant logic principles (Vargo and Lusch, 2004; 2008), it would be interesting to explore how specific Industry 4.0 technological pillars, (i.e., autonomous robots), can co-create value effectively interacting with service customers. Fourth, in light of the direct link between the Industry 4.0 and business model innovation (communities 1 and 2), scholars should leverage on concepts pertaining to the business model innovation literature to comprehend how investments in digital technologies impact the way organisations are designed, conduct their activities and tailor their value proposition to their customers in the service industries. In essence, this will ultimately translate into a better understanding of how companies create, capture and deliver value through the deployment of Industry 4.0 initiatives (Amit and Zott, 2012; Zott and Amit, 2007; Zott et al., 2011). Overall, due to the multiple stakeholders contemporary acting to shape the digital future of the service industries (i.e., governments and digital entrepreneurs), it would be interesting for management researchers to combine some of the aforementioned disciplinary fields and theoretical lenses. This would allow them gaining a comprehensive and holistic understanding of the interactions of different stakeholders for co-creating value within the digitised service industries. Finally, we strongly believe that this would be beneficial to bridge the two nascent innovation research streams looking at the Industry 4.0 in manufacturing (i.e., Hermann et al., 2016; Müller et al., 2018a) and the digital transformation of services (i.e., Rust and Huang, 2014; Huang and Rust, 2018).

2.5.2 Practical implications

The graphical representations of the research front revolving around the Industry 4.0 in management and social sciences, the overarching framework devised in **Figure 13** and the in-depth analysis of services with an Industry 4.0 lens also provide useful practical implications for companies and policymakers.

Referring to businesses aiming to undertake Industry 4.0 initiatives, managers can use the clusters highlighted in **Figure 12** to understand what are the main technologies and themes associated with the new industrial revolution in the manufacturing landscape and delve deeper into specific communities based on their needs. Besides, they can use the conceptual framework in **Figure 13** to generate a more holistic view of how the Industry 4.0 is currently supposed to impact organisations, and link with other economic phenomena and approaches (i.e., circular economy, lean manufacturing). This would ultimately provide useful knowledge for strategic decision making. Finally, related to the growing importance of services, manufacturing companies should carefully think about services surrounding the products they offer, to become provider of Industry 4.0 solutions (Müller et al., 2018a), whereas services companies should pay more attention to the vision, design principles and technological pillars of the Industry 4.0 for designing services complying with the Service 4.0 paradigm (Rehse et al., 2016).

As far as governments and policymakers are concerned, **Figure 2** provides an overview of the current key players supporting innovation activities related to the Industry 4.0 around the globe. This knowledge could be beneficial to compare existing initiatives and their outcomes. However, most notably, governments could find particularly useful the conceptual framework depicted in **Figure 13** since this could help them critically analyse their current initiatives and to better inform their future developmental plans. As such, in line with the transition of the German government from the *Industrie 4.0* to the *Smart Service World* plan, we could expect policymakers to take some steps forward and gradually shift their attention to services and the service industries. Policies and plans in this direction will guide investments for an efficient service innovation that would ultimately allow to capture all the value created by Industry 4.0 initiatives as suggested by the European Commission (2016). In conclusion, the digital transformation of the global economy will drive our society to experience a new hybrid service economy made of Smart Services which merge products and services in a unique bundle (German Federal Ministry, 2017) and a step closer to the materialization of the 4^{th} Industrial Revolution.

2.6 Conclusions and limitations

This paper, investigating the Industry 4.0 phenomenon, makes two relevant contributions. First, the study depicts the intellectual structure of emerging managerial and social sciences literature related to the Industry 4.0 through a systematic quantitative literature review, which is matched with social network analysis. Second, it recognises if and how scholars in management are embedding services and services sectors into the wide Industry 4.0 paradigm. Following a quantitative systematic literature review approach, the manuscript conducts an in-depth examination of the Industry 4.0 paradigm, related plans and projects, and its possible evolution towards the service industries domain.

Focusing on the methodology, the authors decided to adopt a specific bibliometric technique, namely bibliographical coupling, since this approach is able to provide through the use of a network a clear and effective structural image of emerging fields in literature. The findings allow to identify key aspects based on the technological layers singled out by scholars. Based on our results, three main managerial and social sciences streams can be assessed in literature: advanced manufacturing technologies, Industry 4.0 technologies, and additive manufacturing. With the aim of providing an overview of the big picture of the emerging managerial and social sciences literature related to the Industry 4.0 phenomenon, we linked together the themes found into an overarching framework displayed in **Figure 13**. We also specified the unique features of the articles and identified the recurrent theme for each community detected through social network analysis.

As far as the role of services in the Industry 4.0 is concerned, we found that the available managerial literature is still scant. However, we expect a future service orientation to take place as implicitly indicated in recent literature (Müller et al., 2018a). Moreover, although service engineering and management seem to be an important component embedded in the Industry 4.0 (Rennung et al., 2016) there is still a remarkable gap between the manufacturing sector and the service sector (Bienhaus and Haddud, 2018). As a matter of fact, future efforts on the services and service industries are expected, mainly to provide a more comprehensive picture of the impact of Industry 4.0 technologies and design principles in the services domain and its possible consequences on business model innovation.

The novelty of the proposed literature review is firstly related to the fact that, to the best of our knowledge, this is the first attempt to examine the role of services through the lenses of the Industry 4.0 literature. Secondly, part of the novelty is also related to the methodological perspective of the study. In fact, this work leverages a data-driven approach, which is innovative and cannot be found in existing reviews dealing with the Industry 4.0 phenomenon from social sciences and managerial perspectives (Piccarozzi et al., 2018; Schneider, 2018). Furthermore, we carry out a more granular analysis leveraging a wider set of keywords and provide a clear visualization of the thematic clusters of the literature by applying a community discovery algorithm to the results of the bibliometric technique adopted. Thirdly, with the aim of providing a better understanding of the topics dealt with by management and social sciences scholars regarding the 4th Industrial Revolution, we propose a framework that maps out the most substantial findings from the network structure. Despite the fact that the visualization does not claim to be fully comprehensive of all the efforts put in place by managerial scholars, this can be used by academics and practitioners to enhance their knowledge on the main emerging managerial aspects related to the Industry 4.0 and help them to discover original venues for future research on this ongoing industrial revolution.

This research is not without limitations. Despite being part of the novelty of the study, the methodological approach exploited in the analysis exhibits strengths and weaknesses. Indeed, although bibliometric analysis techniques are gaining scholarly consensus as effective methods to map out the structure of the literature in a given field of study, they can display a few drawbacks (Mura et al., 2018). Exclusively relying on citation analysis, bibliographical coupling gives more visibility to articles with a long reference list (Vogel and Güttel, 2013), such as literature reviews. Furthermore, it does not capture the reason that brought some authors to refer to a particular citation (Zupic and Čater, 2015). Furthermore, as a method of dimensionality reduction, the findings significantly depend on the threshold chosen as a cut off to obtain the citation network. For this reason, we tried different thresholds as a robustness check.

Regardless of this methodological limitation, we believe that the study offers a clear understanding of the emerging managerial and social sciences intellectual structure related to the Industry 4.0 phenomenon, highlighting the importance of a future orientation of scholarly attention to services and the service sector and providing useful guidance for further investigations.

Chapter 3: Paper 2.
"Service Robots in Online Reviews: online robotic discourse"

Abstract

Service robots promise to transform the essence of services and in turn customers' experience. However, extant literature lacks empirical evidence on the relevance and characteristics of service robots after consumption. As suggested by previous research, online customers' discourse can be seen as a critical means to evaluate the introduction of new products or services. Thus, building on research and theorizations belonging to the application of electronic Word-Of-Mouth (eWOM) to the diffusion of innovation, this study leverages on online reviews (ORs) to monitor popularity and consumers' awareness of service robots. As such, it develops the concept of online robotic discourse - defined as eWOM in online reviews mentioning explicitly service robots deployed in hospitality services - to track the adoption and diffusion of service robots over time. Following a data science approach, the trends and distributions of ORs reporting service robots are analysed for 19 international hotels pioneering the deployment of service robotics in their frontline operations. The results unveil how service robots are gradually perceived as a popular and distinctive factor in the judgement of service experiences, further than a plain novelty consequence. This suggests that a better understanding of reviewing behaviours and eWOM related to robot-empowered hospitality services can help to enhance scholarly knowledge pertaining to human-robot interactions, and the adoption and diffusion of innovation in the tourism context.

Keywords: Service robots; Online robotic discourse; Online reviews; eWOM; Diffusion of innovation.

3.1 Introduction

The innovation wave brough about the 4th Industrial Revolution is supposed to create new forms of collaboration through the seamless interconnection of humans and machines (Hermann et al., 2016). Indeed, within the services industries human-machines interaction can co-create services (Huang and Rust, 2018) and value (Mariani and Borghi, 2019). Progress in robotics and artificial intelligence has allowed machines to conduct gradually more complex tasks (Wirtz et al., 2018). Due to their physical embodiment and their increased interaction with humans, service robots can be perceived as social agents able to redefine service encounters (Larivière et al., 2017). This is of special interest in the tourism and hospitality sector, where the deployment of service robots is on the rise, promising to disrupt the nature of services and customers' experience (Tussyadiah, 2020).

Yet, to date, scholarly efforts in the tourism and hospitality domain have been rather fragmented and highly conceptual, leaving aside empirical research designs (Ivanov et al., 2019a). According to Tussyadiah (2020) relatively little is known about the assessment of the impacts of intelligent automation on tourism, and more longitudinal studies are needed (Ivanov et al., 2019a) to make sense of the influence of service robots after consumption (Lu et al., 2020). To address the aforementioned call for research, consistently with Godes and Mayzlin (2004), this work builds on electronic word-of-mouth (eWOM) research and theorizations to capture and track the diffusion of innovation by means of online conversations. Previous research has suggested that customers' discourse in online reviews (ORs) is critical upon and immediately after new product introductions to build consumers' awareness (Godes and Mayzlin, 2004) and can be leveraged to track the popularity of a product or service feature over time (Chevalier and Mayzlin, 2006). Therefore, we argue that online consumers' discourse can be a useful means to assess whether the awareness about service robots goes beyond a mere *"novelty effect"* (Roehrich, 2004). Indeed, if the novelty effect associated with service robots is the only mechanism in place, robots' popularity would rapidly fade away, suggesting that robots are not a distinctive factor in the evaluation of the service offering. As service robots have been introduced in hospitality services quite recently, there is an urgent need to explore how and if customers' discourse revolving around them is evolving over time from both a diffusion and adoption of innovation (Rogers, 2003) and a human-robot interaction perspective (Newell and Card, 1985; Tussyadiah, 2020).

To bridge this research gap, this study aims to provide preliminary insights on the following research question: *Are service robots becoming an increasingly distinctive and popular feature in hotel-related eWOM beyond their introduction?* To this end, we develop the concept of *online robotic discourse* - defined as eWOM in online reviews mentioning explicitly service robots deployed in hospitality services - to monitor the diffusion (Godes and Mayzlin, 2004) and adoption (Dellarocas et al., 2007) of service robots over time. This is critical from both a consumer perspective to understand the relevance of service robots in consumers' evaluation of service experiences, and from a company perspective to shed light on the outcomes of innovation strategies. In particular, leveraging on a data science approach (Mariani et al., 2018a; Mariani et al., 2018b; Witten et al., 2016), we deployed a one-factor repeated measures research design (Myers et al., 2010) to capture the popularity of service robots and performed a series of statistical comparisons of OR distributions (Mariani and Borghi, 2018; Mariani et al., 2019; Ransbothan et al., 2019) to assess the distinctiveness of online conversations related to service robots. Accordingly, this work contributes to the emerging research stream at the intersection of eWOM and human-robot interaction (Gretzel and Murphy, 2019; Tung and Au, 2018) with the purpose of using eWOM to track diffusion of innovation (Rogers, 2003) and improve our understanding of the impacts of intelligent automation in tourism (Tussyadiah, 2020).

The manuscript is organised as follows. **Section 3.2** provides an overview of the literature revolving around service robots and highlights the importance of eWOM in innovation research. **Section 3.3** reports the data collection process and the methodologies used. The main findings and the results of the robustness check are presented in **Section 3.4**. The discussion related to the theoretical contributions and practical implications of the study is embedded in **Section 3.5,** where also a research agenda stemming from the deployment of *online robotic discourse* is put forward. Lastly, **Section 3.6** reports the study's conclusions and limitations.

3.2 Related Literature: Service Robots evolution

3.2.1 Robots in different guises: definitions

The word "*robot*" has been officially introduced in the 1920 drama Rossum's Universal Robots (R.U.R) written by the Czech writer Karel Čapek (Bainbridge, 2004). Nonetheless, the true inventor was Karel's brother Josef Čapek who - inspired by the Czech word "*robota*" (forced labour) - coined the term to identify artificial workers in the drama (Margolius, 2017). The concept has gradually evolved over time and in a more technical-fashion a robot can currently be defined as an "*actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks*" (International Organization for Standardization, 2012a: n.p.). Yet, nowadays there exist a wide range of typologies of robots and their definition is entrenched in the context in which they perform their tasks (Tussyadiah, 2020). Indeed, in the manufacturing industries, we refer to *industrial robots* (e.g., Acemoglu and Restepo, 2020; Pillai et al., 2020) and in turn, in the service industries, to *service robots* (e.g., Wirtz et al., 2018) in the broader landscape of automated social presence (see van Doorn et al., 2017).

As part of the manufacturing framework, the international organization for standardization characterizes an industrial robot as "*an automatically controlled, reprogrammable, and multipurpose (machine)*" (International Organization for Standardization, 2012b: n.p.). This definition and the definition of the robots given above, are closely related and mainly refer to the technical functionalities of the machine itself. However, when it comes to the provision of a service, researchers – in the last few years – have taken into account the interaction of robots with an organization's customer (Wirtz et al., 2018), the manifested social presence (van Doorn et al., 2017) and the degree by which a service can be customized (Jörling et al., 2019) to define service robots as a special form of robots and differentiate them in extant literature from other service technologies. Indeed, as stated by Wirtz et al. (2018, p. 909) service robots can be conceived as "*system-based autonomous and adaptable interfaces that interact, communicate, and deliver service to an organization's customers.*" Adding emphasis to its embodiment and customization capabilities, Jörling et al. (2019, p. 405) define service robots as "*information technology in a physical embodiment, providing customized services by performing physical as well as nonphysical tasks with a high degree of autonomy"*.

Combining these different definitions, a service robot – leveraging on its high level of agency and its physical embodiment – can be perceived by a customer as a social agent (van Doorn et al., 2017). Based on this assumption, van Doorn et al. (2017: p. 44) introduced the term "*automated social presence*" defining it "*as the extent to which machines (e.g., robots) make consumers feel that they are in the company of another social entity*". Thus, a robot in the service context is not merely seen as a gear in the assembly line but rather as a social entity that can actively affect the customer experience.

3.2.2 Intelligence meets robotics

Leaving aside domain-specific definitions, autonomous robots are considered one of the nine technological pillars of the innovation wave brought about by the 4th Industrial Revolution (Mariani and Borghi, 2019). The driving force of this socio-technical process is the fusion and interaction of emerging and existing technologies, which will increasingly blur the thin boundary between the biological, digital, and physical domains (Schwab, 2016). To this respect, the gradual infusion of Artificial Intelligence (AI) in autonomous machines delivering services is perceived as a crucial source of innovation in the digital transformation of services (Rust and Huang, 2014).

The combination of intelligence with a robotic agent has brought to life the innovative concept of "*intelligent robot*" which has been defined in the extant literature as a robot that "*has its own environment perception ability and can connect perception and action through independent thinking and can make appropriate actions according to the external environment*" (Lai et al., 2018: p. 450). Therefore, the presence of movement, sensory, and thinking elements make intelligent robots different from ordinary robots (Tussyadiah, 2020). Indeed, sensory and movement elements allow robots to sense and navigate the surrounding environment. However, the thinking element is the one coordinating the perceived sensory-based stimuli and actuating - through the movement elements - the appropriate reaction (Tussyadiah, 2020). The latter element is empowered by AI which can, in its turn, be associated with different levels of "thinking" functionalities. On this premise, exploring the potential development of AI, Huang and Rust (2018) have delineated four different types of AIs, namely, mechanical, analytical, intuitive, and empathetic. These categories are not mutually exclusive and aim to mimic the potential cumulative development of AI, starting with mechanical AI to automate standardized and repetitive tasks until the use of empathetic AI for more high-touch services that require the incorporation of emotions in the service interaction and decision-making process. This framework has been recently simplified into three components – mechanical, thinking, and feeling - to empirically prove that this is the rational process by which AI is driving the economy (Huang et al., 2019). Nonetheless, just mechanical AI has achieved an efficient state of development and it is the one mainly used in the marketplace (Huang and Rust, 2020). This is due to the fact that this kind of machines are rule-based agents that rely on a priori knowledge that governs the reaction to stimuli. Robots embedding mechanical-AI do not understand the circumscribed environment updating their internal knowledge base accordingly, but rather they feed sensory input in already established ad hoc functioning models that are created for stable and repetitive working environments (Engelberger 1989: p. 108-109). On the other hand, thinking AI is a mainstream area of research and feeling AI – the most advanced form of intelligence – needs further developments to be mastered and understood in its essence (Huang and Rust, 2020).

In light of the plethora of definitions provided, the current study refers to the term service robots and intelligent service robots interchangeably. Accordingly, for the purposes of the study as well as for **Chapter 4** of this thesis, we will take into account robots that have sensory and mobility functionalities, interact with the service customer and integrate artificial intelligence elements in their embodiment.

3.2.3 Electronic Word-of-Mouth and service robots

As highlighted by extant literature reviews on service robotics, empirical examinations are largely missing (Ivanov et al., 2019; Tung and Law, 2017; Tussyadiah, 2020) and the few studies performed deploying a quantitative research design mainly leverage on survey and laboratory experimental data (Ivanov et al., 2019; Lu et al., 2020; Tussyadiah, 2020). These sources of data, despite having the power to provide in-depth insights on customers beliefs and attitudes towards service robots, partially disregard the evaluation of service robots from the context where the service experience took place. On the contrary, as suggested by Schuckert et al. (2015) self-reported customers comments, for example ORs, can be considered as a more reliable source of information since online content is posted spontaneously by online users and is less prone to sampling bias. Therefore, the analysis of ORs can let researchers understand whether service robots are considered a *popular* and *distinctive* factor when evaluating the service experience.

In fact, regardless of experimental research designs (Viglia and Dolnicar, 2020), tourism and hospitality scholars have recently started to leverage on self-reported robotic service encounter experiences stemming from eWOM. As stated by Hennig-Thurau et al. (2004) in their seminal work, eWOM indicates any negative or positive statement made by potential, actual or former customers which is available to a multitude of people via the Internet. As part of eWOM, ORs can be defined as "*a type of product information created by users based on personal usage experience*" (Chen and Xie, 2008, p. 477). Essentially, as described by Godes and Mayzlin (2004: p. 558) ORs represent a "*publicly accessible reservoir of observable person-to-person communications*". Researchers in tourism and hospitality have paid significant attention to eWOM since it is a source of information of paramount importance in the tourist decision-making process (Litvin et al., 2008). The main value stems from the co-creation mechanism which allows users to evaluate service providers, while creating at the same time a unique selling proposition for businesses and their brands (Gligorijevic, 2016).

As suggested by the thematic analysis conducted by Kwok et al. (2017) four types of features can be extracted from ORs: quantitative evaluation features, verbal evaluation features, reputation features and social features. Quantitative evaluation features are the core elements that scholars can extract form ORs. As indicated by Godes and Silva (2004), the most important elements of this category are the review rating and the review volume. The former refers to the score associated with the overall judgement of a reviewing guest, whereas the latter indicates the overall number of ORs posted on the OR platform related to that specific product or service (Godes and Silva, 2004). The second category of OR metrics entails verbal evaluation features; these are metrics extracted from the OR text (Kwok et al., 2017). For example, the most prominent indicators in this category is the length of the reviewing text (Park and Nicolau, 2015) that has also been recently linked to the concept of reviewing effort (Xu et al., 2020b). As the third category of OR metrics, we have the reputation features. This group refers to the set of elements related to the profile of the reviewing guest (Kwok et al., 2017). A metric usually deployed from this category to signal the level of expertise of the reviewer is the number of review s/he has posted on the OR platform (Mariani and Borghi, 2018). Finally, social features comprise metrics stemming from the interaction of members in the OR platform. Indeed, in some OR platforms, online readers can provide helpful votes to ORs and managers can actually respond to guests' ORs (Kwok et al., 2017).

As far as robotic service encounter experiences are concerned, Tung and Au (2018) were the first scholars relying on ORs to explore qualitatively customers' perceptions while using service robots across a wide range of human-robot interaction dimensions related to the user experience. The authors, using a small and limited sample of 329 ORs from 4 international hotels with a different degree of robotic adoption, found that robotic service encounters could lead to a new level of experience co-creation since consumers seem to establish a sort of "relationship" with robots. By embracing a netnographic approach to online content including also ORs, Gretzel and Murphy (2019) assessed ideological positions of consumers towards the use of robotics in tourism and hospitality, and found evidence supporting all the four ideological fields studied: techtopian, green luddite, work machine and techspressive. Finally, Yu (2020), examining comments to two robot-related YouTube Videos, highlights how the dimensions of perceived safety, animacy, intelligence, anthropomorphism, and likeability are depicting in a different way the attitude to use service robots. In this case, the author does not directly use self-reported robotic service encounters, but she adopts ORs as a possible expression of that interaction.

Despite these studies' findings, the analysis of online conversations covering service robots deployed in tourism and hospitality services is still in its infancy. Indeed, to the best of our knowledge, no study has yet analysed quantitatively self-reported robotic service encounters using eWOM contained in ORs. This is surprising as capturing customers' discourse in ORs is critical upon and immediately after new product introductions (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Godes and Silva, 2004; Liu, 2006). In the mainstream marketing literature, there is an established link between research using eWOM data to explore the diffusion of innovation. For instance, Godes and Silva (2004) were among the first scholars to study online conversations related to the introduction of new television shows. The authors state that this source of information can be used as a cost-effective proxy to measure WOM. Besides, when extracting dimensions from online conversations, Godes and Silva (2004) refer to the volume of eWOM as a measure of consumers' awareness of a new product or service. The more the conversations, the more consumers will become informed about it. This view has also been followed by Liu (2006) in his research about the impact of eWOM on box office revenue of newly released movies. Nonetheless, in their study of book sales through Amazon.com, Chevalier and Mayzlin (2006) suggest that review volume is a good indicator of product popularity among online readers. As such, if a new product/service is associated with a higher number of reviews (i.e., higher OR volume), customers are likely to buy more of the new product/service. To further corroborate this argument, extending diffusion of innovation research, Dellarocas et al. (2007) specifically considered eWOM related metrics as valuable indicators to measure customers' adoption of innovation. Based on this theoretical ground we introduced the novel concept of *online robotic discourse* - defined as eWOM in online reviews mentioning explicitly service robots deployed in hospitality services - to monitor the diffusion (Godes and Mayzlin, 2004) and adoption (Dellarocas et al., 2007) of service robots over time.

In particular, leveraging on *online robotic discourse* we should be able to understand whether a novelty effect (Roehrich, 2004) is the only mechanism in place when customers decide to evaluate service robots in their reviews. Indeed, some scholars (Mende et al., 2019; Ivanov et al., 2019) have argued that the introduction of service robots can be associated to a novelty effect (Roehrich, 2004). As discussed by Roehrich (2004) through the concept of *consumer* *innovativeness,* or "consumption of newness", there seems to exist a specific consumer category (e.g., early adopters) that possesses the tendency of buying new products or being attracted by them. As such, in line with Mende et al. (2019) and Ivanov et al. (2019a), if the introduction of service robots is solely linked to a novelty effect, we would then expect a sharp increase in the ORs mentioning service robots in the months immediately after the introduction of the service robot. However, this effect would rapidly fade away over time if service robots are not perceived as a valuable feature of the hotel stay experience (worth to be mentioned in an OR) and would be mirrored in a gradually declining trend of ORs covering service robots.

As robots have been introduced in hospitality services quite recently, there is an urgent need to explore how and if customers' discourse revolving around service robots is developing over time. Exploring online conversations covering service robots by means of eWOM and ORs is critical as eWOM influences customers' behaviours (Fang et al., 2016), firms' performance (Mariani and Visani, 2019; Viglia et al., 2016; Yang et al., 2018) and companies' strategy (Chen and Xie, 2008), allowing consumers to become co-marketers (Filieri and McLeay, 2014). Interestingly, while online conversations about service robots have been mentioned by hospitality managers as a driver of customer engagement (de Kervenoael et al., 2020) in qualitative research, quantitative large sample analyses on customers are largely missing. As such, this chapter of the thesis aims to examine empirically and quantitatively ORs mentioning service robots trying to discern whether they are a *popular* and *distinctive* feature in online conversations.

3.3 Methodology

3.3.1 Data collection

Based on a data science approach (Bi et al., 2019; Mariani et al., 2018a; Witten et al., 2016), we analyse quantitatively the distribution of ORs covering service robots over time and across a wide range of hotels that have adopted robots in their frontline services. In particular, the data collection phase is made of three different steps. Firstly, we conducted an online research on the most popular search engine worldwide – Google – using keywords related to different types of robots in the hotel domain combined with the search term "hotel", to detect leading hotels adopting service robots in their operations. In terms of robot-related keywords we used those described by Ivanov et al. (2017), such as, concierge robot, robot butler, luggage robot, and front-desk robot. This led us to create a list of potential candidate hotels for our final sample. Secondly, we performed further research for each hotel found during the first search step, triangulating content on their website, company news, social media accounts and company reports to identify the introduction date and the name of the robot. From this preliminary sample, we only selected hotels which had a TripAdvisor account and for which we were able to understand the specific period for the deployment of service robots. This allowed us to identify 19 international hotels (see **Table 9**). Thirdly, we retrieved the entire population of TripAdvisor ORs for the 19 hotels identified in the exploratory research until October 2019. The automatic translation function of TripAdvisor was used to homogenise the language of the retrieved content to English. Accordingly, we obtained a total sample of 49,209 reviews of which 27,433 were written after the introduction of service robots. As far as the OR features are concerned, we collected the text of the OR to be able to understand whether the reviewing guest mentioned service robots when evaluating the service experience. Moreover, we collected a set of quantitative metadata related to the OR, such as the overall rating, the number of embedded pictures and the number of reviews written in the OR platform. This set of features has been used by other researchers (see, i.e., Mariani et al., 2019) to understand whether different sub-samples of ORs systematically differ.

Finally, to avoid infringing any general data protection regulation (GDPR) and any potential damage to the hotels and reviewers identified for the purposes of the research (Corti et al., 2019), we have decided to perform a data anonymisation task at the hotel and reviewer level (Monkman et al., 2018). This led us to assign anonymous identifiers to each and every hotel and review for the purposes of the analysis. For this reason, we do not report the hotel name in any of the tables and figures and aggregate the hotel location at the continent level in **Table 9**. The same logic has been applied for the data collected for **Chapter 4** of this thesis.

Table 9. *Summary of hotels that introduced robots in their frontline operations*

Hotel ID	Hotel Continent	Type of Robot
Hotel 1	North America	butler
Hotel 2	North America	butler
Hotel 3	North America	butler
Hotel 4	Asia	front desk, luggage, room assistant, concierge, butler
Hotel 5	North America	concierge
Hotel 6	North America	butler
Hotel 7	Asia	butler
Hotel 8	North America	butler
Hotel 9	Asia	butler, chef
Hotel 10	Europe	concierge
Hotel 11	Asia	butler
Hotel 12	North America	security
Hotel 13	North America	butler
Hotel 14	North America	butler, luggage, concierge
Hotel 15	Asia	butler
Hotel 16	North America	butler
Hotel 17	North America	butler
Hotel 18	North America	luggage
Hotel 19	Asia	butler

3.3.2 Methods

As far as the methods used in this study are concerned, we first deployed a one-factor repeated-measures design (Myers et al., 2010) conducting a longitudinal analysis to understand the importance of service robots during the evaluation of the stay. Second, we tried to discern whether the online discourse related to service robots was significantly different from other ORs statistically analysing differences in the distributions (Mariani and Borghi, 2018; Ransbothan et al., 2019).

Regarding the one-factor repeated-measures design, as suggested by Myers et al. (2010), we leveraged on this specific setting to be able to track the importance of service robots in different moments of time. To this end, to capture hotel customers' online discourse related to service robots, we organized the information about TripAdvisor ORs after the introduction of service robots (N=27,433) into two subsamples: one including all the robot-related ORs (N=3,627) and the other encompassing all the remaining reviews (N=23,806). The former were named "*robot-related online reviews*" because they explicitly referred to the robotic service encounters as they either contained the keyword "robot" or the specific name of the robot in the full text of the retrieved review. Based on these two subsamples, we calculated the impact of robot-related ORs for each month after the introduction of service robots in companies' operations. To this aim, we used the percentage of robot-related ORs over the total number of ORs written in the OR platform in a specific month (Mariani et al., 2019). This allowed us to obtain the share of service robots related content in different moments of time (Myers et al., 2010). In econometric terms, this sequence of measurements ordered by a time parameter is defined as a time-series (Yaffee and McGee, 2000). To obtain smoother time-series we combined each monthly observation to create the cumulative percentage of robot-related ORs for each hotel in the sample starting from the first month after the introduction of service robots in the companies' operations. The cumulative percentage constitutes the *one-factor* in our research design. Connecting this set of indicators, we were able to understand the trend of robot-related ORs for each business embedded into the final analysis. Yet, to provide a unified basis for our analysis, we graphically depict each trend starting from the first month of service robot's introduction (see **Figure 16** in **Section 3.4.1**). This temporal shift allowed us to depict a precise trend related to the deployment of service robots in their first 18 months. Further, based on the recommendation of Yaffee and McGee (2000), we calculated the average time series using the simple mean across the analysed businesses. This helped us provide a more robust and comprehensive view of the overall popularity of service robots. However, transcending from the visual analysis of time-series, we employed the Friedman's Chi-Square and Mann-Whitney-Wilcoxon tests to statistically assess whether differences at the hotel and robot levels exist. These two tests, based on the chosen research design and measure (cumulative percentage), have been proven to produce the most effective and reliable results (Myers et al., 2010).

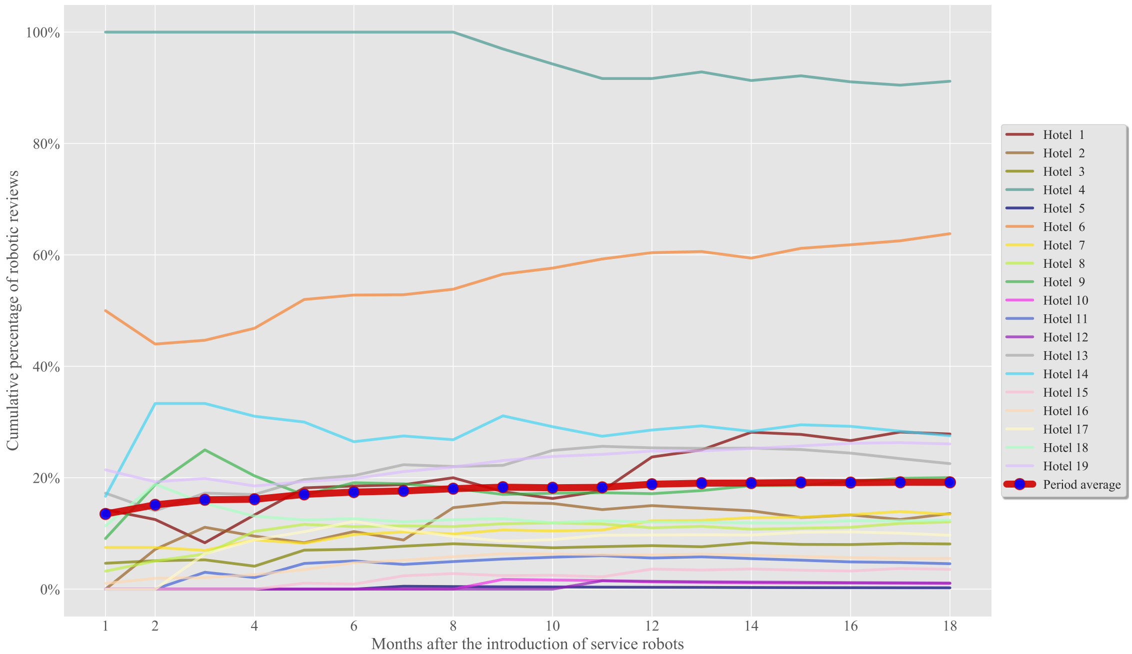
As far as the distinctiveness of *online robotic discourse* is concerned, we build on extant research in service marketing leveraging on eWOM data (Mariani and Borghi, 2018; Mariani et al., 2019; Ransbothan et al., 2019). Accordingly, we compared the distribution of robot-related vs. not robot-related ORs through the deployment of statistical tests. More specifically, we employed both mean (Welch two samples t-test) and median (Mann-Whitney-Wilcoxon test) statistical tests (see, Ransbothan et al., 2019). This provided us a solid statistical basis to claim whether *online robotic discourse* embedded distinctive features. In terms of metrics evaluated, we took into account quantitative evaluation, verbal evaluation and reputation features. As far as the quantitative evaluation features are concerned, we used the review valence that corresponds to the overall score provided by the reviewing guest to judge her stay. This indicator can be used as a proxy of customer satisfaction (Chen et al., 2018). Moreover, we compared the number of images embedded in the ORs and the length of the OR text. As suggested by Xu et al. (2020b), the latter can be seen as a proxy of reviewing effort and belongs to the verbal evaluation features category (Kwok et al., 2017). Finally, at the reviewer's reputation level, we compared the reviewer experience using the number of contributions posted by the reviewer in the OR platform (Mariani and Borghi, 2018). Indeed, it is well known in the mainstream marketing literature that judgements of novice and expert consumers usually differ (Bendapudi and Berry, 1997). This could potentially hold also referring to service robots. For the purposes of the analysis, we used the logarithmic transformation of the number of reviewers' contributions due to the high skewness of the distribution of this variable. Overall, we focus on this parsimonious set of features for the analysis since they are among the core ones extracted by researchers using eWOM data (Cantallops and Salvi, 2014; Kwok et al., 2017). Thus, finding statistical differences in this set of indicators can highlight the distinctiveness of *online robotic discourse*.

3.4. Findings

3.4.1 Trend of online robotic discourse

In relation to the analysis of the share of robot-related ORs, **Figure 16** presents the cumulative percentage of robot-related ORs for each hotel in the sample starting from the first month after the introduction of service robots into the companies' operations. As is clear from **Figure 16**, there are differentiated trends of *online robotic discourse* across the 19 different hotels; however, the average trend (the red dotted line) is increasing over time. More specifically, in the first month after the introduction of service robots, on average 13.5% of ORs contained the evaluation of robotic service encounters. This figure raises up to 19.2% after 18 months, meaning that almost one out of five reviewers included service robots in the judgement of their stay. More specifically, looking at the slopes of the average trend line from the 1st to the 6th month, robotic reviews augment by 3.93%. From the 7th to the 12th month there is an increase of 1.41%, and a further increase by 0.33 between the 13th and 18th month. Interestingly, the growth rate is higher in the first months after the robots' introduction, and it continues being positive, but lower, one year after the introduction of service robots. This result suggests that service robots are not merely linked to a *novelty effect* (Roehrich, 2004), but rather that after their introduction they have become a distinctive factor in the evaluation of the service experience. Moreover, performing a series of Friedman's Chi-Square tests we found statistically significant differences in the entire sample ($\chi^2 = 312.19$, $p < 0.001$) and also across hotels having introduced only one type of robot ($\chi^2 = 236.23$, $p < 0.001$). This corroborates the idea that the way the hotel designs the service experience revolving around service robots matters towards the inclusion of service robots in the evaluation of the stay (Ivanov et al., 2019). More broadly, it could be seen as a valuable insight to confirm the fact that firm characteristics impact the deployment of service robots as suggested by Xiao and Kumar (2019). Furthermore, aggregating hotels based on the two main service robots identified in the dataset (i.e., robot butler and concierge), the Mann-Whitney-Wilcoxon test showed a significant difference between the samples ($z = 5.14$, $p < 0.001$). Indeed, robot butlers seem to have a higher impact in terms of mentions (mean = 17.58%) than concierge robots (mean = 0.63%) on the *online robotic discourse*. This could be due to robot butlers being more likely than concierge robots to co-create customized experiences (Tung and Au, 2018).

Figure 16. *Trend of online robotic discourse in eWOM in the first 18 months*



3.4.2 Differences in robot vs. not robot-related ORs

By comparing the two subsamples, a wide range of statistically significant differences can be detected (see **Table 10**). Indeed, all the statistical tests deployed (either Welch two samples t-test and Mann-Whitney-Wilcoxon test) found statistically significant differences ($p < 0.001$) for each of the analysed dimensions.

Table 10. *Comparison of robot vs. not robot-related ORs entire sample*

	Total Sample (N=27,433)		**Robot-related ORs** (N=3,627)		**Not robot-related ORs** (N=23,806)		**t-test**	**Mann-Whitney-Wilcoxon test**
	Mean	SD	Mean	SD	Mean	SD	t	$Wx10^7$
Valence	4.264	1.002	4.356	0.871	4.250	1.020	6.699^{***}	4.469^{***}
Review Images	0.294	0.876	0.497	1.097	0.263	0.833	12.316^{***}	4.711^{***}
Review Length (in words)	109.384	105.696	151.738	145.672	102.943	96.592	19.570^{***}	5.421^{***}
Log(Reviewer Experience)	2.359	1.859	2.760	1.907	2.298	1.844	13.721^{***}	4.922^{***}

Notes: * $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$

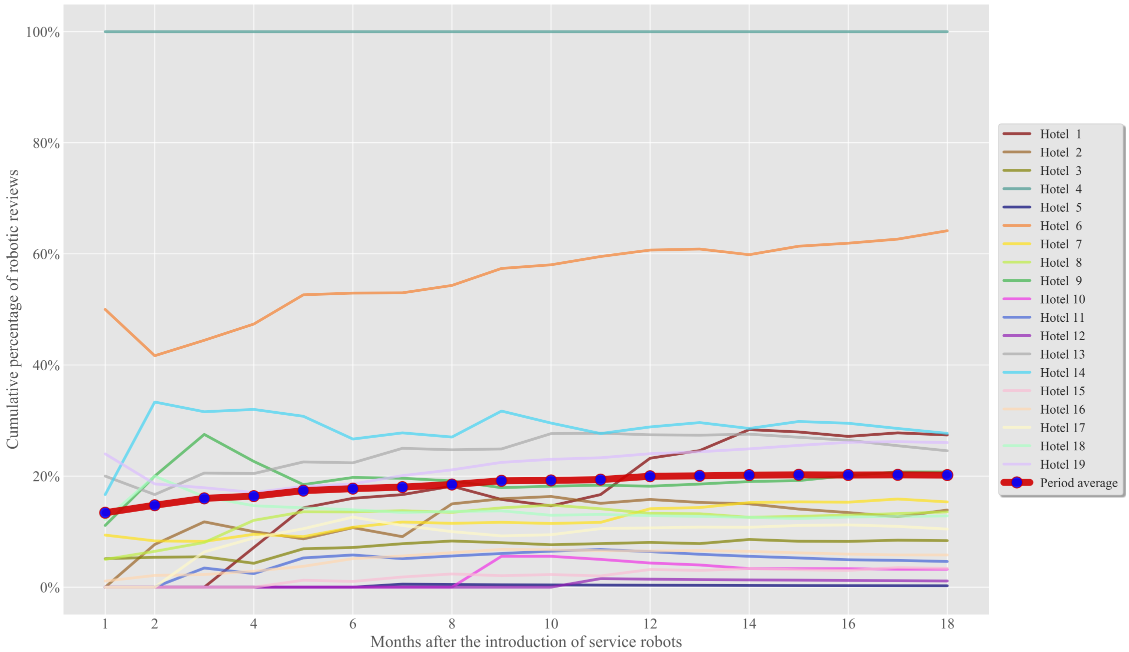
First, robot-related ORs display higher ratings (4.356) than not robot-related ORs (4.250). Moreover, robot-related ORs are less extreme than their counterparts since their standard deviation is lower than the rest of the ORs. Despite unequal sample sizes, these differences might suggest that the integration of robots might be associated with more positively-valenced eWOM. The reason might be that travellers are curious about and positively impressed by the innovation brought about by robots (Tung and Au, 2018). Second, reviewers reporting service robots are keener to embed images in their ORs. An explanation of this finding could be that reviewers might find it easier to describe a robot-related visual content or they might want to provide further evidence of robots' presence using photos in online communities (Lo et al., 2011).

Third, focusing on the textual content, robot-related ORs are significantly longer than not robot-related ORs, with the former consisting on average of approximately 150 words and the latter of around 103 words. We might infer that aspects related to robots are normally covered by more detailed reviews that report more information on different hospitality service attributes. Finally, it seems that more experienced reviewers are more prone to mention service robots than their counterparts. Since volume can be perceived as a proxy of awareness (Godes and Mayzlin, 2004) in the introduction phase, more active and experienced reviewers might know in advance about the presence of the robot and therefore we expect that their experience will be more influenced by the robotic service encounter.

3.4.3 Robustness Check

Since the main results could potentially be subjected to machine translation errors (Lucas et al., 2014), we performed the same set of analysis presented in **Sections 3.4.1** and **3.4.2** on the sample of ORs written in English. This sampling criterion led us to use a subsample of our original sample consisting of 21,616 ORs, with 2,959 robot-related ORs and 18,657 not-robot related ORs, for this robustness check.

Figure 17. *Trend of online robotic discourse in eWOM in the first 18 months after service robots' introduction English sample*



As depicted by **Figure 17**, the cumulative percentage of service robots ORs follows approximately the same trends of the overall sample, supporting and strengthening the main findings of the research. Indeed, even in this scenario, starting from a 13.4% share during the first month after the introduction of service robots, the share reaches a 20.18% value after 18 months, with the highest increase between the 1st and 6th month (4.34%). Besides, the Friedman's Chi-Square test found statistically significant differences both in the entire subsample ($\chi2$= 301.836, $p < 0.001$) and for hotels having introduced only one type of service robot ($\chi2$= 221.254, $p < 0.001$). Furthermore, the Mann-Whitney-Wilcoxon test presented a significant difference between hotels having introduced robot butler vis-à-vis concierge robot (z= 5.137, $p < 0.001$). Indeed, robot butlers are mentioned on average in 18.15% of the subsample, compared to a mere 1.73% for concierge robots. Overall, the findings from the analysis of the English ORs subsample further confirm the main results of the longitudinal analysis.

Table 11. Comparison of sub-distributions of robot vs. not robot-related ORs English subsample

	Total Sample (N = 21,616)		**Robot-related ORs** (N = 2,959)		**Not robot-related ORs** (N = 18,657)		**t-test**	**Mann-Whitney-Wilcoxon test**
	Mean	SD	Mean	SD	Mean	SD	t	W x 10^7
Valence	4.259	1.035	4.39	0.868	4.238	1.057	8.559^{***}	2.908^{***}
Review Images	0.247	0.805	0.433	1.029	0.218	0.759	10.922^{***}	2.995^{***}
Review Length (in words)	111.997	110.603	152.14	149.048	105.631	101.758	16.379^{***}	3.399^{***}
Log(Reviewer Experience)	2.175	1.869	2.604	1.913	2.107	1.853	13.721^{***}	3.175^{***}

Notes: * $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$

Regarding the distinctiveness of *online robotic discourse*, as clear from **Table 11** all the analysed dimensions are found to be statistically different (either by the Welch two samples t-test and Mann-Whitney-Wilcoxon test) between the sub-distributions of robot vs. not robot-related ORs in the English subsample. As such, all the results are in line with the main findings based on the overall sample of ORs.

3.5 Discussion

3.5.1 Theoretical implications

Within the service marketing literature, this work contributes to the emerging research stream at the intersection of eWOM and human-robot interactions (Gretzel and Murphy, 2019; Tung and Au, 2018).

On the one hand, this study extends previous research looking at the diffusion of innovation with analytics stemming from the analysis of online conversations (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Godes and Silva, 2004; Liu, 2006). Indeed, to the best of the authors' knowledge, this is the first study quantitatively analysing a large sample of ORs collected from hotels having introduced service robots in their operations. Thus, the fact that we found higher ratings associated with robot-related ORs supports studies claiming that service robots can enhance customer experience (Ivanov and Webster, 2019a; Tung and Au, 2018). Moreover, since more experienced reviewers are more willing to evaluate service robots, we could argue that the different judgemental behaviour postulated by Bendapudi and Berry (1997) between expert and novice consumers still holds in relation to service robots. Interestingly, by combining the findings related to reviewer experience and the length of the review, with the stream of literature related to OR helpfulness (Mariani and Borghi, 2020; Mudambi and Schuff, 2010), we may conjecture that ORs mentioning service robots are among the most impactful in the online community. Indeed, the degree of helpfulness of ORs has been found to be positively associated with more informative (longer in terms of words) content (Fang et al., 2016; Mudambi and Schuff, 2010) redacted by expert reviewers (Cheng and Ho, 2015; Park and Nicolau, 2015). These relationships have been confirmed by the extant meta-analytic investigation on the determinants of OR helpfulness performed by Hong et al. (2017). Finally, being associated with a higher number of user-provided photos, we might infer that robot-related ORs could have a higher potential in shaping traveller's perception. Indeed, as suggested by Lo et al. (2011) the combination of visual and textual contents can enrich the narratives of online reviewers and help them transform an intangible experience into a tangible one.

On the other hand, building on research and theorizations related to the application of eWOM to the diffusion and adoption of innovation, we first introduce and develop the concept of *online robotic discourse*. This construct is then used to demonstrate through a longitudinal research design how service robots' awareness and popularity are increasing over time. These findings seem to theoretically suggest that the novelty effect associated with service robots (Roehrich, 2004) is not the only mechanism in place when customers decide to interact with robots. Indeed, service robots seem to be perceived as an important element of the service offering by a multitude of customers and not only by those guided by the tendency of trying new/different products. Therefore, we can argue that service robots can have a crucial role in the hotel marketing mix since reviewing guests are increasingly evaluating this feature in the judgement of their stay (Wirtz and Lovelock, 2018). Besides, assessing differences at the hotel level, this study corroborates theoretical arguments that suggest a relationship between the deployment of service robots and firm characteristics (Ivanov et al., 2019; Xiao and Kumar, 2019).

3.5.2 Practical implications

This research bears practical implications for both hotel and OR platform managers. At the hotel managerial level, if we combine our results with those of de Kervenoael et al. (2020), it seems that the marketing efforts made by companies to promote service robots have paid off. Indeed, the level of awareness of service robots in the online platform community is growing over time. However, most notably, this work highlights the increasing popularity of service robots during the evaluation of the service experience and its potential association with higher ratings. Hence, we could expect that hotels pioneering the introduction of service robots in their operations could be soon followed by their competitors. Yet, our insight on the impact of service robots on customer ratings should be assessed by more comprehensive studies using econometrics models, extant theorizations related to customer satisfaction, and potentially also by conducting field experiments (e.g., Viglia et al., 2019). Nonetheless, since it seems that reviews mentioning service robots are generally more informative in relation to textual and visual contents, and written by more experienced reviewers, hotel managers should therefore critically evaluate them. This is because the abovementioned traits make them highly influential in the online community (Hong et al., 2017). Accordingly, robot-related ORs may involve different response strategies (Lui et al., 2018). Besides, in light of the importance to collect and analyse feedback related to service robots (Xu et al., 2020a), eWOM data could be seen as an effective means to achieve this goal. Indeed, as suggested by Filieri and McLeay (2014), reviewing guests can act as co-marketers. As such, it would be crucial for hotels to evaluate online conversations revolving around service robots to improve the effectiveness of this kind of innovation in their operations. In fact, reviewers could provide useful suggestions and/or highlight the reasons why they were satisfied/dissatisfied with a specific robotic service encounter.

Regarding OR platform managers, they might decide, in a relatively close future, to explicitly include also "robotic service experience" as a suitable category/attribute for consumers to assess their experience. This would further help hotel managers to understand quantitatively the outcomes related to the introduction of service robots in their operations. Besides, OR platforms might decide to provide a specific section on the hotel profile page where the hotel can promote the introduction of robots, for example using pictures and videos. Due to the importance of OR platforms in the consumer decision-making process, this would increase the level of awareness of consumers about service robots. Indeed, even consumers not engaging in in-depth research either consulting the hotel web page or a wide range of ORs, would be aware of the presence of service robots in hotel's operations.

3.5.3 Research Agenda

In essence, the concepts and preliminary insights put forward by this study can provide useful ground for future research on service robotics in different research streams. Indeed, by deploying the novel concept of *online robotic discourse*, tourism and hospitality researchers could use these online conversations (Godes and Mayzlin, 2004) about robots and the related analytics (Mariani, 2019) to (1) inform research pertaining to the diffusion and adoption of innovation (Rogers, 2003) involving service robots; (2) inform research related to human-robot interactions (Newell and Card, 1985) in the tourism context (Tussyadiah, 2020).

As far as (1) is concerned, as different customer groups adopt differently innovation and the adoption behaviours change over time, scholars could use *online robotic discourse* to generate insights on robots' diffusion and adoption across different categories of travellers. This will provide useful insights for companies aiming to customize their service offerings at the individual level. Furthermore, a more in-depth analysis of *online robotic discourse* can help researchers generate knowledge about tourism companies' introduction, adoption, and deployment processes of service robots that might be relevant to optimize companies' operations. This could provide important implications in the literature on operations management.

As far as (2) is concerned, *online robotic discourse* can aid scholars to understand how and to what extent service robots drive and influence customers' evaluations of (and satisfaction with) tourism and hospitality services, whereby evaluation can be captured by means of OR ratings. Due to the paramount importance of customer satisfaction in the tourism and hospitality research domain (Bi et al., 2020), this would be a top priority for researchers in the field. Besides, this could be important for the literature at the intersection of service marketing and operations management, since the impact of service robots on customer satisfaction can truly reveal whether this type of automation is solely bringing a productivity gain (Rust and Huang, 2012). Furthermore, *online robotic discourse* can assist researchers interested in analysing service encounters (Larivière et al., 2017) allowing them to gain knowledge about robots-enabled tourism and hospitality service encounters. Finally, and related to the previous point, *online robotic discourse* would help researchers disentangle the assessment of intelligent automation in tourism and hospitality services from a more objective and less biased perspective.

3.6 Conclusions

This exploratory study on *online robotic discourse* reveals how service robots are increasingly becoming a recurrent and popular feature in the evaluation of the hotel stay, beyond a mere novelty effect. This suggests that service robots are perceived as valuable not only by travellers interested in service innovation, but also by an increasing number of service customers. Additionally, it corroborates the idea that service robots distinctively impact the tourist experience as we found statistically significant differences between the robot-related and not robot-related samples of ORs. Nonetheless, heterogeneity in reviewing behaviours exists across the hotels and robots reviewed.

This work has some limitations. Our results stem from data retrieved from a single OR platform (TripAdvisor) for a convenience sample of leading international hotels at different stages of service robots adoption in frontline services and the selected firms display high variance in terms of scope of the adoption in the company. Accordingly, supplementary empirical research might be conducted on other OR platforms to warrant a better generalisation of our results. Besides, this goal could also be achieved using a larger sample of hotels embedding service robots in their operations. Finally, to further generalise the current findings to the broad tourism and hospitality domain, scholars could take into account different types of business except for hotels.

Chapter 4: Paper 3.
“Exploring the impact of service robots on customer satisfaction: an empirical investigation leveraging online reviews”

Abstract

The gradual infusion of artificial intelligence in autonomous machines delivering services (i.e., service robots) is perceived as a crucial source of innovation in the digital transformation of services. Yet, service scholars seem to have empirically overlooked the impact of service robots in the overall evaluation of the service experience. To bridge this gap, drawing upon the three-factor theory of customer satisfaction applied to electronic Word-Of-Mouth data, the manuscript aims to capture the effect of service robots on customer satisfaction, under the guise of online review (OR) ratings. To this end, a penalty-reward contrast analysis built upon text analytics techniques is performed on a sample of almost 70,000 TripAdvisor ORs covering 44 international hotels embedding service robots in their operations. The results show that positive performance associated with service robots outweighs the impact of negative one on customer satisfaction, suggesting that service robots are an “Excitement factor” (or satisfier) in the three-factor framework of customer satisfaction. Thus, hotel managers should confidently embrace service robots in their operations to pursue differentiation strategies. Further robustness checks deploying a quasi-experimental research design, through propensity score matching, validate the study’s findings.

Keywords: Service robots; Customer satisfaction; Online reviews; Asymmetric effect; Propensity score matching.

4.1 Introduction

The 4th Industrial Revolution is expected to profoundly change the contemporaneous society (Schwab, 2016). Cyber-physical systems, as a novel general-purpose technology, will generate unprecedented value, coupling digital and physical processes (Liao et al., 2017). This phenomenon can be observed also in the service industries (Mariani and Borghi, 2019) and more specifically the tourism domain (Stankov and Gretzel, 2020). Within the service realm, artificial intelligence and robotics are perceived as the main driving forces of the digital transformation of services (Rust and Huang, 2014; Jörling et al., 2019). Indeed, these technologies not only allow businesses to increasingly automate their processes, but they do also have the potential to redefine the interaction with service customers (Larivière et al., 2017).

The global market for professional service robots is rising at an exceptional pace. As reported by the International Federation of Robotics (2018; 2019), from the 59,269 units sold for professional use to businesses in 2016, the figures in 2018 went up to more than 271,000 units, reflecting a stunning 475 per cent increase. As from the latest forecasts, sales are supposed to ultimately hit a 7 digits figure in 2022, reaching an estimated amount of 1,019,300 units (International Federation of Robotics, 2019) while prices are predicted to decrease at a 5 per cent annual rate (Financial Times, 2020). In the tourism and hospitality domain, international hotel brands such as Hilton, Marriott, and YOTEL are leading the digital transformation of services (Business Traveller, 2017), and are expected to be soon followed by several other companies (ASD Report, 2019). To date, service robots in the hotel setting have been deployed in a wide range of roles, acting as concierge, porter, room assistant, butler, housekeeper, and even as a front-line employee (Ivanov et al., 2017).

This remarkable growth in the demand for service robots worldwide did not go unnoticed in academic literature, where a sharp increase of interest has been recorded especially in the last five years (Ivanov et al., 2019). Scholars have started to question the role of service robots, exploring consumers' perceptions in terms of trust (Tussyadiah et al., 2020), attribution of responsibility (Jörling et al., 2019), acceptance (de Kervenoael et al., 2020), attitude (Ivanov et al., 2018a; 2018b), service failure (Fan et al., 2020) and human-like morphology (Mende et al., 2019). Yet, this blooming research field is rather fragmented (Lu et al., 2020) and dominated by conceptual contributions (Ivanov et al., 2019, Tussyadiah, 2020). As such, service researchers have started to call for empirical investigations (Marinova et al., 2017; Rafaeli et al., 2017), in which tourism and hospitality scholars should pay particular attention to the influence of service robots on "*the tourist*" experience (Tung and Law, 2017). As stressed by Lu et al. (2020), further investigation is needed in the post-service encounter consumption phase in order to shed light on the influence of service robots on perceived overall service quality and customer satisfaction. This is a remarkable research gap in light of the perennial tourism and hospitality scholars' quest for unveiling which attributes of the service offering are more appreciated by service customers

(Dolnicar and Otter, 2003). Indeed, being able to satisfy the customer is seen as "*the key to the success of every organization in the hospitality field*" (Bi et al., 2020: p. 1). Besides, shedding light on the impact of automation on perceived satisfaction can provide useful insights in the literature at the intersection of service marketing and operations management, pondering if the widely acknowledged trade-off between productivity and customer satisfaction still exists (Rust and Huang, 2012; Wirtz and Zeithaml, 2018). In fact, automation is supposed to bring productivity gains, but does not always imply higher satisfaction levels (Rust and Huang, 2012). If service robots are found to play a positive and significant role either in terms of productivity and customer satisfaction it could be argued that they constitute an effective pathway to achieve differentiation strategies at a lower unit cost or a form of *cost-effective service excellence* (Wirtz and Zeithaml, 2018). This is even more important due to the established difficulties that historically managers have experienced to efficiently innovate (Martin-Rios and Ciobanu, 2019).

With the objective of filling the abovementioned research gap, building on extant theorization of customer satisfaction and research revolving around human-robot interaction, this study aims to answer the following research question: *To what extent do service robots influence perceived customer satisfaction in the hotel industry?*

To this end, due to its superior explanatory power (Bi et al., 2020), the three-factor theory of customer satisfaction represents the main theoretical framework of the study. Based on this underpinning, distinctively from other studies, this work examines online review (OR) data related to a sample of 44 international hotels having introduced service robots in their operations. Through a Penalty-Reward contrast analysis, innovatively conceived deploying text analytics measures, the impact of service robots' evaluation pertaining to overall customer satisfaction and service quality is explored at different levels of performance (i.e., positive or negative). Finally, to further assess the validity of the results, the study leverages on a quasi-experimental contrast analysis, namely propensity score matching. Employing this technique, a more balanced sample is obtained, which – to a certain extent – simulates a randomized controlled trial to reduce the biases related to the estimates' results. In sum, the study aims to extend scholarly knowledge at the intersection of the evaluation of the service experience, human-robot interaction, electronic Word-Of-Mouth, and operations management.

The manuscript is structured as follows. **Section 4.2** provides an overview of the literature revolving around service robots and delves deeper into the literature pertaining to customer satisfaction showcasing the main research proposition and hypotheses the study aims to test. A description of the data collected, and methodology deployed is presented in **Section 4.3**, whereas **Section 4.4** reports the main findings of the study and the robustness checks performed. In **Section 4.5** theoretical contributions and practical implications are discussed. Finally, **Section 4.6** embodies the conclusions and limitations of the study, suggesting avenues for future research.

4.2. Related Literature: Service Robots and Customer Satisfaction

4.2.1 Extant studies on service robots

The introduction of service robots in the marketplace has witnessed a sharp increase of interest in services marketing research (Wirtz et al., 2018) and tourism and hospitality academic literature (Ivanov et al., 2019).

As pointed out by Ivanov et al. (2019) in their systematic literature review, seven relevant research domains can be associated with the aforementioned trend: 1) robot; 2) human; 3) robot manufacturer; 4) tourist company; 5) servicescape; 6) external environment; 7) education, training and research. Only recently tourism and hospitality scholars have tried to explore the novel area of human-robot interaction (Murphy et al., 2017). Indeed, digging in-depth into the human-robot interaction framework, especially on the dimensions of presence and embodiment, Tung and Law (2017) suggested that future researchers should pay particular attention to the influence of service robots on "*the tourist*" experience. The authors' results have been corroborated by the latest call for research on artificial intelligence and robotics in tourism conceived by Tussyadiah (2020) where "Assessing the Impacts of Intelligent Automation in Tourism" is seen as a fruitful avenue for future research aiming to unpack the impact of service robots on society. Thus, it will be particularly important to gain knowledge related to the performances of the human-robot interaction for researchers and practitioners.

Hitherto, extant research on service robots is rather fragmented (Lu et al., 2020) and dominated by conceptual contributions (Ivanov et al., 2019) that have brought about the notion of robotic service encounter (Jörling et al., 2019) and the conceptual analysis of the degree of robotic adoption in frontline services (Ivanov et al., 2017; van Doorn et al., 2017; Wirtz et al., 2018; Xiao and Kumar, 2019; Marinova et al., 2017; Rafaeli et al., 2017). In essence, based on scholarly definitions of service robots (see Jörling et al., 2019; Wirtz et al., 2018), it appears that the latter ones integrate sensory, movement, and thinking elements in a physical embodiment (Tussyadiah, 2020) and can effectively interact with the service customers (Lu et al., 2020). Therefore, they can be perceived as a social entity more than a simple machine embedded in companies' operations (van Doorn et al., 2017).

To gain more knowledge about service encounters involving service robots and customers, scholars in service research have recently generated several empirical investigations. For instance, Jörling et al. (2019) demonstrate how different levels of internal and external attribution of responsibility can influence differently the performances of robotic service encounters. Surprisingly, the authors' results suggest the existence of an inverse self-service bias. Indeed, responsibility for robotic encounters associated with low levels of performance was found to have a higher probability to be attributed internally (e.g., to the service customer rather than the robot). Nonetheless, the sense of control provides a suitable moderation effect in the relationship between the attribution of responsibility and the levels of performance in a robotic encounter (Jörling et al., 2019). Bringing anthropomorphism into the picture, Mende et al. (2019) assess how human-like morphology of service robots can elicit discomfort and thus intensify compensatory responses in consumers. However, Tussyadiah and Miller (2019) proved how robotic technologies can effectively be deployed to promote sustainable consumers behaviours. Fan et al. (2020) went further, exploring how the level of dissatisfaction with service robots is moderated by the consumers' level of technology self-efficacy and interdependent self-construal. Interestingly, Tussyadiah et al. (2020) find that travellers' trust in robots is not affected by the physical form of the robots but rather by attitude, propensity to trust, and beliefs towards technology. Furthermore, de Kervenoael et al. (2020) demonstrate that the intention of using service robots in the hospitality context is not solely related to technology acceptance factors (e.g., Davis, 1989; Venkatesh et al., 2003) and service quality elements, but it is also associated with empathy and information sharing within human-robot interactions.

Yet, all the aforementioned studies leveraged on survey data, observational experiment, and laboratory experiment, not taking into account self-reported service encounters and disregarding – *de facto* – the service robot in the context of the overall service experience. Thus, as stressed by Lu et al. (2020) further investigation is needed in the post-service encounter consumption phase in order to shed light on the influence of service robots on perceived overall service quality and customer satisfaction. This is a remarkable research gap, and we aim to bridge it using electronic Word-Of-Mouth (eWOM). Indeed, it is widely acknowledged in the mainstream marketing literature the importance of analysing customers' discourse in ORs upon and immediately after a new product or service introduction (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Godes and Mayzlin, 2004; Liu, 2006). Nonetheless, within the academic literature related to service robots, the stream of research that uses online conversations covering service robots is still in its infancy (Borghi and Mariani, 2020; Gretzel and Murphy, 2019; Tung and Au, 2018). Borghi and Mariani (2020), in the first quantitative examination using ORs, introduced the concept of *online robotic discourse* defined as *"eWOM in online reviews mentioning explicitly service robots deployed in hospitality services*" (Borghi and Mariani, 2020: p.1). As suggested by the authors *online robotic discourse* can aid scholars to understand the impact of service robots in companies' operations. As such, we build on *online robotic discourse* to empirically analyse a large sample of unbiased, self-reported service encounters trying to discern to what extent service robots influence customers' overall satisfaction with the entire service offering.

The next section introduces the concept of customer satisfaction, the evolution of the frameworks proposed to measure it, and the research proposition and hypotheses we aim to test in this study.

4.2.2 Customer Satisfaction with services

Customer satisfaction represents a complex construct in academic literature whose nature has evolved over time (Anderson et al., 2004; Oliver, 1981). Overall, it can be perceived as a psychological concept revolving around the feeling of pleasure and well-being stemming from the consumption activities of a product and/or service (World Tourism Organisation, 1985). Several literature streams have tried to provide an explanation of the origin of the concept. In the mainstream marketing literature, according to the expectation-disconfirmation theory (Oliver, 1977; 1980; 1981), satisfaction is a unidimensional concept which arises as a cognitive comparison between expectations and actual product/service performance (Cadotte et al., 1987). Thus, satisfaction is defined on a single continuum, having at its extremities satisfaction and dissatisfaction, respectively. Therefore, a performance exceeding the pre-purchase expectations leads to customer satisfaction and, in contrast, a performance lower than expectations results in dissatisfaction. However, a few years later, drawing on Bradburn's (1969) affect-balance theory, Oliver (1993) introduced the "attribute basis" of satisfaction. The idea is that different facets of a product or service act simultaneously towards the construction of the overall satisfaction. Indeed, the complex nature of a service encounter can evoke either positive and negative affective reactions which are associated with different features (or attributes) of the service experience (Derbaix and Pham, 1991). Following Oliver's steps, in the context of hospitality enterprises, Pizam and Ellis (1999) suggested a compensatory model related to customer satisfaction. The authors introduced a weighted and non-weighted version of their model based on how the consumer makes judgments revolving around satisfaction. On the one hand, the weighted model simply implies the association of an importance level to each service feature by the customer. On the other hand, the non-weighted model entails that a trade-off logic is leveraged by the customer when expressing satisfaction with the service offering. In this case, dissatisfaction originated by a service attribute can be compensated by the satisfaction provided by another feature, as long as the latter presents a higher level of importance.

However, the unidimensional nature of satisfaction has been challenged by research in the quality management literature, having at its root the motivation-hygiene theory proposed by Herzberg et al. (1959) in the context of job satisfaction (Pizam and Ellis, 1999). The theory states that satisfaction and dissatisfaction are not the extremes of the same continuum but rather the extremes of two distinctive continua. The absence of dissatisfaction (satisfaction) will not automatically cause satisfaction (dissatisfaction). In other words, satisfaction and dissatisfaction are seen as different dimensions. The framework defines two independent sets of factors: satisfiers (motivator) and dissatisfiers (hygiene)[3]. Motivator factors are the ones which cause

[3] Factors were named hygiene and motivator due to the fact that the empirical context of the study of Herzberg et al. (1959) was job satisfaction. In particular, "hygiene" stands for those extrinsic elements to

satisfaction (e.g., opportunities for professional growth) that, however, if not provided, do not originate dissatisfaction. Conversely, the so-called hygiene factors are associated with the core features of a product or service that, if not performing well, can cause dissatisfaction, but whose improvement does not lead to satisfaction (e.g., working conditions and environment).

Building on Herzberg et al. (1959) two-factor theory, Kano et al. (1984) were the first to devise a multi-factor structure that encompasses the effect of service attributes on customer satisfaction. The authors suggested five quality dimensions in which to classify service features: must-be quality, one-dimensional quality, attractive quality, indifferent quality, and reverse quality. Compared to the factors of Herzberg et al. (1959), must-be quality identifies dissatisfiers whereas attractive quality refers to satisfiers. The real innovation in the model is embedded in the introduction of the one-dimensional and the reverse quality dimensions which comprise factors that act in both the satisfaction and the dissatisfaction continua. Indeed, the one-dimensional quality category includes features positively correlated to customer satisfaction, whose absence causes dissatisfaction and whose presence originates satisfaction. The mechanism underlying reverse quality elements works exactly the other way round. Besides, indifferent quality includes features that do not generate any noteworthy influence on customer satisfaction. Looking into the details, an important peculiarity of the Kano et al. (1984)'s model is represented by its dynamic nature which allows attributes to change classification over time. This could be the reason for its wider adoption in several academic fields (Matzler et al., 2004). For instance, as stated by Gregory and Parsa (2013), when attractive elements become commonalities in the marketplace, they may potentially shift to the one-dimensional category, hence becoming basic elements. Nonetheless, in the quality management literature, the Kano et al. (1984)'s model, despite having five quality dimensions, is usually adopted as a three-factor framework, where satisfiers refer to attractive quality, dissatisfiers to must-be quality, and hybrids to one-dimensional quality (Gregory and Parsa, 2013). The exclusion of reverse and indifferent elements might be related to the fact that the research area which largely embraced this framework has been the research line on product/service development and improvement (Ting and Chen, 2002).

The three-factor theory has only recently gained momentum and consensus among researchers in the customer satisfaction domain (Anderson et al., 2004; Füller and Matzler, 2008; Oliver, 1997). As reported by Füller and Matzler (2008) the reasons could lie in the support it has found during the 90s by studies identifying asymmetric effects of product (e.g., Mittal et al., 1998) and service (e.g., Johnston, 1995) attributes on overall satisfaction and its adoption by popular writers of that time (e.g., Vavra, 1997). Delving deeper into its structure, as asserted by Matzler

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the job itself that are considered maintenance factors, such as supervision, company policies, interpersonal relationships, status and salary (Herzberg, 1968).

and Sauerwein (2002), the three-factor framework of customer satisfaction encompasses three distinctive sets of dimensions:

- **Basic Factors (or dissatisfiers):** this category includes features whose absence leads to dissatisfaction but whose presence does not elicit satisfaction, even though they are provided with a high-level standard. Basic factors are into the backbone of the product/service offering and are essentially expected by the customers; however, their fulfilment is an insufficient condition towards satisfaction. The relationship between these factors' performance and satisfaction is asymmetric since high-level performance implies a lower gain in terms of overall satisfaction than low-level performance. This category refers to the "must-be quality" dimension in the Kano et al. (1984)'s model.
- **Performance factors (or hybrids)**: this set of elements lies in both satisfaction and dissatisfaction continua: if performance is high (low) they can lead to satisfaction (dissatisfaction). Thus, the relationship between performance and overall satisfaction for this kind of feature is both symmetric and linear. They translate into the one-dimensional quality factors in the Kano et al. (1984)'s model.
- **Excitement Factors (or satisfiers)**: these factors can be a source of satisfaction if fulfilled, but their absence does not lead to dissatisfaction. There is an asymmetry in the relationship between overall satisfaction and attribute performance. Indeed, a low-level of performance has a lower effect on satisfaction compared to a high-level of performance for factors in this set. Fundamentally, as these elements are able to positively surprise the customers, they have also the capabilities to eventually evoke "delight" (Rust and Oliver, 2000). In other terms, in the Kano et al. (1984)'s model, excitement factors correspond to attractive quality elements.

The reasoning and articulation revolving around the three-factors framework do not only provide a useful structure for academic researchers, but they also have meaningful implications when applied to managerial practices (Matzler and Hinterhuber, 1998). To this respect, on the one hand basic factors are perceived as the pillar for any company which has the aim to enter in that specific market, and, on the other hand, performance elements set the bases of competition in that market. Finally, excitement factors are the ones directly linked to differentiation strategies which allow firms to be distinctive from other competitors. If we look at this classification schema from both the service marketing and operations management perspectives, as argued by Rust and Huang (2012) it could be difficult for organisations to embed excitement factors improving customer satisfaction, while simultaneously limiting financial expenses. Indeed, as expressed by Rust and Huang (2012: p. 47) "*service productivity often involves a tradeoff, with better service typically requiring more labor intensity, lower productivity, and higher cost*". However, challenging this argument, Wirtz and Zeithaml (2018) identify a set of core strategies that could lead organisations to conjointly achieve customer satisfaction and productivity gains. Thus, being able to classify a factor through the classification schema provided by Matzler and Hinterhuber (1998) can potentially help researchers understand their wider impact on companies' operations and strategies.

In the tourism and hospitality research domain, after the seminal contribution of Cadotte and Turgeon (1988) who suggested the existence of an asymmetric effect of service attributes on customer satisfaction, there has not been enough support to further verify the validity of their results, using the novel three-factor framework of customer satisfaction (Pizam et al., 2016). Nonetheless, the study by Alegre and Garau (2010) confirmed the view of Cadotte and Turgeon (1988) testing different frameworks of customer satisfaction. Based on Alegre and Garau' (2010) findings, other researchers have gradually started exploring the impact of several service features on overall customer satisfaction, deploying the three-factor framework of customer satisfaction as their reference conceptual model. For instance, Lu and Stepchenkova (2012) assessed the influence of 26 service attributes in the context of ecotourism and Gerdt et al. (2019) evaluated the effect of the 27 "Global Sustainable Tourism Criteria for Hotels and Tour Operators" in the context of eWOM. Besides, Bi et al. (2020) investigated the impact of service attribute performance among different types of travellers, continents, and hotel categories.

Yet, to the best of the authors' knowledge, no study has tried to examine the impact - in terms of overall satisfaction with the service offering - of the introduction of service robots in companies' operations. The next section puts forward arguments to classify service robots in the three-factor framework of customer satisfaction.

4.2.3 Service robots in the three-factor Framework of customer satisfaction

This section tries to collocate service robots into the three-factor framework of customer satisfaction looking at this form of innovation from two different angles: service innovation and human-robot interaction perspectives leveraging on the attribution theory. In the broad landscape of service innovation literature, the introduction of a new service, through its technological novelty, is expected to provide a competitive advantage to the company introducing it (Evangelista and Vezzani, 2010). As highlighted by Hjalager (2010) this expectation holds also in the tourism and hospitality industry. In particular, as depicted in the comprehensive literature review performed by Gomezelj (2016), innovation activities and behaviours seem to be positively correlated with firm performance, productivity, quality standards and firm value. However, the recent study of Martin-Rios and Ciobanu (2019) suggested that for tourism firms only complex innovations, embedding technological and non-technological forms of innovation, have a positive impact on company performance. Conceptually, service robots can be considered as a complex innovation (de Kervenoael et al., 2020) since they not only provide a new or improved service delivery method (technological element), but also modify the division of work inside the company and the way the firm promotes itself (non-technological elements). As such, the introduction of service robots could have a positive impact on firm performance, especially on a non-financial performance indicator such as customer satisfaction. This reasoning is supported by extant studies in service robotics where the sense of novelty and uniqueness perceived by the service customer during the robotic service encounter can result in the co-creation of innovative experiences (Tung and Au, 2018) that can exceed customer expectations (Stock and Merkle, 2018) and, in turn, originate customer delight (Oliver et al., 1997). Indeed, service robots are expected to enhance the service delivery process, making it more "*funny and entertaining*" (Ivanov and Webster, 2019a). This conceptual view has been corroborated by Tung and Au's (2018) empirical findings which suggested a positive and pleasant surprise associated with the interaction with service robot described as a "*wow factor*". Thus, in this case, the introduction of service robots can arouse a higher sense of pleasure for the service customers that, in turn, can exceed tourists' expectations. Therefore, leveraging on the innovation literature (Evangelista and Vezzani, 2010; Gomezelj, 2016; Hjalager, 2010; Martin-Rios and Ciobanu, 2019), the attribute can be considered an excitement factor in the three-factor framework of customer satisfaction.

Yet, the interaction with service robots in not prone to failures (Fan et al., 2020) and can elicit negative emotions (Tung and Au, 2018). To this respect, the influence of performance valence has been extensively examined referring to the attribution theory (Miller and Ross, 1975), investigating to whom the service customer attributes the responsibility of the performance (Jörling et al., 2019). In this context, previous research has highlighted the existence of a self-serving bias, conceptualized as the tendency to attribute negative performance externally (e.g., to the service robots) and positive performance internally (e.g., the service customer) (Miller and Ross, 1975), which has been empirically found in different settings (Moon, 2003). In other terms, when a failure happens in a machine-based encounter, the customer is more likely to attribute the responsibility of the negative performance to the machine, hence emphasising the dissatisfaction with the service offering. In light of this asymmetry in attribution behaviours, service robots could be seen as acting also in the dissatisfaction continua. Thus, we can potentially consider them as either "performance factor" or "basic factor" based on the magnitude of the effect. Nonetheless, extant research revolving around human-robot interaction failed to find support for self-serving bias in a robotic service encounter. Conversely, researchers identified the opposite effect either in the hospitality context observing anthropomorphic service robots (Fan et al., 2020; Merkle, 2019) or in the wide service literature examining non-anthropomorphic intelligent robots (Jörling et al., 2019). The reason could lie in the fact that during a robotic service encounter, travellers perceive the robot as a social entity (van Doorn et al., 2017). This perception has the capability to positively strengthen the bond between the service customer and the machine itself (Aaker, 1997; Verhagen et al., 2014), building – to a certain extent – a "relationship" between them (Tung and Au, 2018). On the basis of this effect, travellers could be more prone to attribute the responsibility of a negative service performance internally (i.e., to themselves) (Moon, 2003), which, in turn, could alleviate the dissatisfaction with a service failure (Choi and Mattila, 2008). Reasonably, even in presence of a negative performance stemming from a robotic service encounter, the overall satisfaction related to the service experience should not be significantly affected by the robotic service failure. As a result, merging the innovation literature and extant empirical findings in robot-human interaction studies, we argue that:

Research Proposition: *Service robots in the context of the three-factor framework of customer satisfaction can be classified as an excitement factor*.

Accordingly, based on the aforementioned research proposition, the study aims to test the following two research hypotheses:

Hypothesis 1: *A positive performance stemming from a robotic service encounter significantly increases the overall satisfaction of a service customer with the service experience.*

Hypothesis 2: *A negative performance stemming from a robotic service encounter does not significantly affect the overall satisfaction of a service customer with the service experience.*

4.3 Data

4.3.1 Empirical Context and Data Collection

In terms of the empirical sample, we decided to use ORs for hotels which have embedded service robots in their operations. This choice was guided by the fact that OR data are "*considered more objective, immense, and without sample bias, because reviews are posted spontaneously without laboratory effects unlike traditional questionnaires*" (Schuckert et al., 2015: p. 143). Besides, the adoption of this peculiar content allowed us to assess the impact of service robots in respect to the overall service experience since reviewers are asked to express their overall judgement of their stay.

Since the adoption of service robots in the tourism and hospitality domain is still quite limited (Ivanov and Webster, 2019b), the first challenge that we faced was related to finding hotels that have deployed service robots worldwide. Accordingly, we conducted an extensive online research combining keywords associated with service robots in the hotel domain (see Ivanov et al., 2017) with the search term "hotel", on the leading worldwide search engine Google[4]. This led us to create a list of potential candidate hotels embedding service robots in their operations for our final sample. Secondly, in order to collect further information about the service robots deployed (such as introduction date and robots' name), we performed further research for each hotel identified in the first step. To this aim, we triangulated material available in the company reports, website and social media profiles and news about the company. From this preliminary sample, we only selected hotels which had a TripAdvisor account and for which we were able to understand the specific period for the deployment of service robots. Based on the aforementioned exploratory search and selection criteria a sample of 44 hotels were used as the overall sample for this study. In line with extant research (Tuomi et al., 2020b), the hotels recognized are mainly located in Asia and North America as clearly depicted in **Table 12**, which displays location and type of service robots introduced for each hotel selected. Thirdly, we collected the entire population of ORs made publicly available on TripAdvisor. The latter was selected as it is the largest community-based OR platform and because ORs hosted on the platform influence company performance (Yang et al., 2018). Moreover, during the data collection process, we simulated the interaction of an English user on TripAdvisor to collect – through the automatic translation function made available on the OR platform – the English translation of ORs not written in English. Despite automatic translation techniques being prone to errors (Lucas et al., 2014) this allowed us to homogenise the language of the entire sample and use it to further assess the goodness of the empirical results. This step of data collection was

[4] In the search market, Google controls over the 75% of the shares (https://www.searchenginejournal.com/seo-101/meet-search-engines/)

carried out in November 2019. Therefore, for the purposes of the project, only ORs published in the reviewing platform before October 2019 (included) were retained for the empirical analyses. In terms of volume, we collected 69,497 ORs representing the entire population of ORs on TripAdvisor for the 44 international hotels identified in the first search step. Yet, for the final empirical sample, we decided to select solely user generated contents created after the hotel's adoption of service robot. This choice was made to ensure that the service robot was part of hotel's operations during the guest's stay. In light of the communication efforts made by the hotel to promote this service innovation (de Kervenoael et al., 2020), the assumption is that guests should have been able to interact with (and potentially evaluate) service robots when reviewing their stays. Besides, due to the importance of the travel type dimension during a robotic service encounter (i.e., Tung and Au, 2018) and its impact on customer satisfaction (Bi et al., 2020), we retained only ORs that reported the travel type. These sampling criteria led us to leverage on a sample of 32,985 ORs for the econometric analyses. Referring to the features collected, for each OR we captured verbal, reputation and quantitative evaluation features (Kwok et al., 2017), namely the text of the review and the provided rating, as well as features related to the reviewer profile, for instance her level of experience in the reviewing platform. Furthermore, at the hotel level, we collected a series of metadata available on TripAdvisor, such as the star rating and chain information.

Table 12. *Sample of hotels identified during the online search (Chapter 4)*

Hotel ID	Hotel Location	Service robots deployed
Hotel 1	North America	Butler
Hotel 2	North America	Butler
Hotel 3	North America	Butler
Hotel 4	North America	Butler
Hotel 5	North America	Butler
Hotel 6	North America	Butler
Hotel 7	Asia	Butler
Hotel 8	Asia	front desk, luggage, room assistant, concierge, butler
Hotel 9	North America	Butler
Hotel 10	North America	Butler
Hotel 11	North America	Concierge
Hotel 12	North America	Butler
Hotel 13	North America	Concierge
Hotel 14	North America	Butler
Hotel 15	Asia	Butler
Hotel 16	North America	Butler
Hotel 17	North America	Butler

Hotel 18	North America	Butler
Hotel 19	North America	Butler
Hotel 20	Asia	butler, chef
Hotel 21	Asia	Butler
Hotel 22	Europe	Concierge
Hotel 23	Asia	Butler
Hotel 24	Asia	Butler
Hotel 25	Asia	Butler
Hotel 26	Asia	Concierge
Hotel 27	North America	Butler
Hotel 28	Asia	front desk, luggage, room assistant, concierge, butler
Hotel 29	North America	Butler
Hotel 30	North America	Butler
Hotel 31	Asia	Butler
Hotel 32	North America	Butler
Hotel 33	North America	butler, luggage, concierge
Hotel 34	Asia	Butler
Hotel 35	North America	Butler
Hotel 36	North America	Butler
Hotel 37	North America	Butler
Hotel 38	North America	Butler
Hotel 39	North America	Butler
Hotel 40	North America	Butler
Hotel 41	Asia	Butler
Hotel 42	North America	Luggage
Hotel 43	North America	Butler
Hotel 44	Asia	Butler

4.3.2 Operationalization of the focal variables

In order to assess the existence of an asymmetric relationship between the deployment of service robots in the hospitality setting and customer satisfaction, under the guise of the online rating, we leveraged on the penalty-reward contrast analysis (PRCA) introduced by Brandt (1987). This technique has been found to provide reliable results in a wide range of application fields (Albayrak and Caber, 2013) and it has been recently adopted in the context of ORs (Bi et al., 2020). Essentially, the purpose underlying the adoption of PRCA is to assess the impact of service attributes at different levels of performance (i.e., positive or negative) through the introduction of dummy variables in a regression analysis (Albayrak and Caber, 2013). As such, for the focal service attribute under investigation, namely service robots, two dummy variables were conceived. On the one hand, as the penalty variable, *Robot Neg* identifies situations where unfavourable performances related to the performance of a service robot's interaction occurred. On the other hand, *Robot Pos*, under the guise of the reward variable, refers to situations where a favourable performance materialized. To operationalize the aforementioned measures, following an automated process, we leveraged on recent progress in big data analytics, especially related to advanced text analytics techniques. More specifically, we first used the text of the review to understand whether the reviewing guest used service robots to express her satisfaction with the service experience. To this aim, we extracted from each review the portion of text directly mentioning service robots. Second, analysing the semantic relationships and meanings contained in the latter extract of text, we tried to devise the level of performance associated with service robots. In this manner, we were able to capture whether service robots were perceived as a value-added attribute by the service customer.

The main theoretical underpinning to support the deployment of text analytics techniques to classify the OR text (i.e., robotic or non-robotic review) is based upon the seminal work of Sapir (1944) and Whorf (1956) at the intersection of science and linguistic. In this regard, we leverage on the Sapir-Whorf hypothesis which postulates that the words used in the narrative of an individual written text enclose their cognitive categories. Thus, in line with Sridhar and Srinivasan (2012), we argue that the text reported by online reviewers is primarily related to their service experiences and, hence, to those service attributes that contributed towards the formation of their assessed level of satisfaction.

As suggested by extant literature encompassing big data analytics and eWOM (Alaei et al., 2019; Bi et al., 2019), we measured the performance associated to the focal service attribute (i.e., service robot) through the overall sentiment polarity score (i.e., sentiment strength) extracted from the fragments of text related to the analysed aspect. Sentiment analysis is "*an automated process of examining semantic relationships and meaning in reviews*" (Alaei et al., 2019: p. 175). In particular, we followed the methodology highlighted by Bi et al. (2019) for selecting the portions of texts mentioning service robots and the recommendations of Alaei et al. (2019) on which sentiment analyser to apply. Thus, based on the punctuations, we first divided each OR into a set of sentences, then we aggregated all the sentences containing at least a keyword related to the focal service attribute (i.e., service robots) into one sentence (Bi et al., 2019). We considered the latter as the portion of text directly related to the *evaluation of service robots*. In line with Tung and Au (2018), we used the word "robot" and the name of the robot as robot-related keywords. To ensure reliability, an external researcher manually examined a random sample of 800 ORs evaluating whether they refer to service robots. This process led to an overall agreement in 98.8% of the cases with the computer-based algorithm deployed to extract the sentences related to service robots.

At this stage, in order to obtain the sentiment polarity score for a specific piece of text we had to select the most suitable sentiment analysis technique. Since it is out of the scope of the manuscript to create an ad-hoc text corpus for sentiment analysis purposes, we chose to adopt an existing built-in machine learning algorithm. As argued by scholars adopting the three-factor framework of satisfaction (e.g., Lu and Stepchenkova, 2012; Gerdt et al., 2019), the performance classification task can be treated as a multiclass problem with the aim of identifying "favourable", "unfavourable" and "no comment" categories. In the last category we include either ORs mentioning the robot with a neutral sentiment score and ORs not mentioning the robot at all. This reasoning is underpinned by the reasonable assumption that due to the important marketing efforts produced by businesses to promote the introduction of service robots (de Kervenoael, 2020) and the increasing awareness about this type of innovation among service customers (Borghi and Mariani, 2020), the latter should have known about the presence of service robots and had the opportunity to experience and interact with them during their stay. Accordingly, on the ground provided by one of the latest study of Alaei et al. (2019) - who compared and assessed a wide range of sentiment analysis techniques in the tourism and hospitality domain – we exploited the Valence Aware Dictionary for sEntiment Reasoning (VADER) method (Hutto and Gilbert, 2014) which achieved the highest performance results in the multiclass classification scenario. VADER comprises a sentiment lexicon made of more than 7,500 lexical features where each element has been associated with a value in terms of sentiment intensity. The VADER sentiment lexicon has been validated by humans and targets text especially from social media (such as ORs). For computing the sentiment polarity score, the technique exploits its lexicon combined with a series of syntactical and grammatical heuristics. The score ranges on a bilateral continuum having as extremes: -1 (extremely negative) and +1 (extremely positive), with 0 representing neutral statements (Hutto and Gilbert, 2014).

Thus, the two dummy variables related to the performance related to a service robot encounter were operationalized as follows for each single OR retrieved:

$$Robot\ Pos = \begin{cases} 1, & Sentiment\ of\ Robot\ statement > 0 \\ 0, & Otherwise \end{cases}$$

$$Robot\ Neg = \begin{cases} 1, & Sentiment\ of\ Robot\ statement < 0 \\ 0, & Otherwise \end{cases}$$

Based on the realisations, in terms of econometric coefficients, of the abovementioned two dummy variables, scholars adopting PRCA have developed classification schemes able to effectively allocate attributes in the three-factor framework of customer satisfaction. For example, Lin et al. (2010) proposed a classification method based on the statistical significance of the econometric coefficients as follows:

- A factor can be classify as "Basic Factor" if the dummy related to negative performances (e.g., *Robot Neg* in this case) is significant and the dummy related to positive performances (e.g., *Robot Pos* in this case) is not statistically significant.
- A factor can be classified as "Performance Factor" if either the dummy related to positive performances and the dummy related to negative performances are statistically significant.
- A factor can be classified as "Excitement Factor" if the dummy related to positive performances is significant and the dummy related to negative performances is not statistically significant.

In the literature review about PRCA performed by Albayrak and Caber (2013) this method is considered among the classification techniques that scholars can choose to effectively map attributes in the three-factor framework of customer satisfaction. Thus, *Robot Pos* and *Robot Neg* were used as focal factors in the econometric model illustrated in the following section.

4.3.3 Model Specification

To conduct the empirical examination, testing the two focal hypotheses, we decided to deploy an ordered logit model. The choice was guided by the fact that the dependent variable (i.e., the *Overall Review Rating*) is ordered, discrete and not normally distributed (Sridhar and Srinivasan, 2012). Indeed, TripAdvisor lets online reviewers express their satisfaction through an ordinal scale of five consecutive values: "Terrible"=1, "Poor"=2, "Average"=3, "Very Good"=4, "Excellent"=5. As highlighted by Agresti (2010), ordinal regression approaches, accounting for the "floor effect" and the "ceiling effect", provide less biased estimates compared to linear regression analyses (i.e., Ordinary Least Square) in presence of ordinal categorical dependent variables. Among ordinal regression models, the two most used methods are the logit and probit, which differ for the assumptions made regarding the distribution of the error terms (Zhang et al., 2016). In this regard, following the lead of researchers in marketing and tourism management examining online ratings (e.g., Gao et al., 2018; Godes and Silva, 2012; Stamolampros et al., 2019; Zhang et al., 2016), we opted for the ordered logit model, implicitly assuming that the error term distribution can be approximated by a logistic function.

More specifically, representing with $Rating^*_{rh}$ the continuous latent variable corresponding to the latent overall review rating assigned by reviewer *r* to the hotel *h*, the econometric specification of the model estimated is:

$$\begin{aligned} Rating^*_{rh} = \quad & \beta_0 + \beta_1 Robot\ Pos_{rh} + \beta_2 Robot\ Neg_{rh} + \\ & \beta_3 Observed\ average\ rating_{rh} + \beta_4 No\ Identity\ Disclosure_r + \\ & \beta_5 Reviewer\ Contribution_r + \beta_6 Mobile\ Submission_{rh} + \\ & \beta_7 Overall\ Sentiment\ Polarity_{rh} + \beta_8 Review\ Length_{rh} + \end{aligned} \qquad (1)$$

$$\beta_9 Chain_h + \theta_1' Travel\,Type_{rh} + \theta_2' Year_{rh} + \theta_3' Star\,Rating_h + \theta_4{}' Hotel\,ID_h + \epsilon_{rh}$$

where ϵ_{rh} is the error term at the individual review level, and by which the final observed satisfaction rating $Rating_{rh}$ is calculated in the following manner:

$$Rating_{rh} = \begin{cases} 1 & if \quad -\infty < Rating^*_{rh} \leq k_1 \\ 2 & if \quad k_1 < Rating^*_{rh} \leq k_2 \\ 3 & if \quad k_2 < Rating^*_{rh} \leq k_3 \\ 4 & if \quad k_3 < Rating^*_{rh} \leq k_4 \\ 5 & if \quad k_4 < Rating^*_{rh} < +\infty \end{cases}$$

In the abovementioned rules, the different realisation of the variables (i.e., values from 1 to 5) corresponds to the scores allowed by TripAdvisor, whereas k_1, k_2, k_3, k_4 represent the set of four cut-off points determined by the model. The latter are used to discern the specific discrete ordinal response from the predicted latent rating. In this process, the model implicitly assumes the values of $-\infty$ as the lower bound and $+\infty$ as the upper bound among the cut-off points (Cameron and Trivedi, 2005). Accordingly, the region of probability between two consecutive cut-off points represents the probability of observing a certain $Rating_{rh}$. Stated more formally, the predicted probability of a given observation is determined as follows:

$$\Pr(Rating_{rh} = i) = \Pr(k_{i-1} < Rating^*_{rh} < k_i) \quad , with\ i\ \epsilon\{1,2,3,4,5\}$$

where *i* refers to the set of discrete outcomes and $k_0 = -\infty$ and $k_5 = +\infty$. Further details of the chosen estimation technique can be found in Agresti (2010), and Cameron and Trivedi (2005).

For the purposes of the study, in **Equation 1**, our main interest was related to the coefficients β_1 and β_2, which correspond to the reward (*Robot Pos*) and penalty (*Robot Neg*) dummies, specifically crafted to test the two proposed hypotheses. In addition to the focal independent variables, as clearly depicted by **Equation 1**, we decided to introduce a series of control variables which, in extant eWOM literature , have been found to play a remarkable role in influencing customer satisfaction with a given service. This allows for a more comprehensive model specification which helps improving the reliability of the findings. The next section describes the control indicators used in the analysis.

4.3.4 Control Variables

According to extant eWOM literature, a wide range of metrics have been found to significantly impact the overall rating provided by an online reviewer. Therefore, in our model specification, we embedded a set of control variables related to the reviewer, platform, content, company and temporal dimensions. More specifically, at the *platform-level*, since reviewers have been found to be socially influenced by previous online ratings posted on the OR platform (Sridhar and Srinivasan, 2012), we included the average rating observed by the reviewer prior to submitting her own judgement of the hotel experience (*Observed average Rating*). As far as the reviewer-level is concerned, in line with Gao et al. (2018), we embedded in the econometric model the effect of reviewer experience (*Reviewer Contribution*), using the number of contributions in terms of number of posts on the OR platform. This is due to the fact that a novice judges a service differently from an expert (Bendapudi and Berry, 1997). Moreover, according to Forman et al. (2008) the level of information disclosed by online reviewers can have an effect on their online rating behaviours. Therefore, we developed a dummy variable (*No Identity Disclosure*) as a control, assuming the value of 1 when the reviewer had not disclosed either gender or age (Gao et al., 2018). Besides, since the device used to submit the OR can affect reviewing behaviours (Mariani et al., 2019; Rosario et al., 2019), we introduced a dummy variable (*Submission Device*) in order to distinguish between smartphone (or tablet), and desktop computers.

Furthermore, following extant research referring to the impact of textual OR cues on customer satisfaction, we capture the effect of overall polarity of the reviewer text (*Overall Sentiment Polarity*) and the length of the review text (*Review Length*). The underlying reason is that there seems to be a positive correlation between review sentiment and the OR ratings (Geetha et al., 2017), and the longer reviews are more likely to be associated with negative ratings (Poncheri et al., 2008). Besides, controlling for the *Overall Sentiment Polarity* allows to set the correct reference point in terms of overall content polarity for every analysed review. This is of paramount importance when assessing the impact of service robots since it helps to effectively discern whether the focal service attribute analysed stands out from the evaluation of the service offer. Moreover, we control for the purpose of the trip (*Travel Type*) and the year (*Year*) (Bi et al., 2020; Godes and Silva, 2012). Finally, we capture potential heterogeneity at the hotel-level, controlling for the hotel star rating (*Star Rating*), the fact that the hotel belongs to a chain (*Chain*) and further, including an individual hotel identifier (*Hotel ID*).

Table 13 briefly reports the description of all the variables deployed in the econometric analysis, whereas **Table 14** displays their descriptive statistics. Looking in detail at the figures in **Table 14**, the collected ORs show an average review rating (4.289) in the upper end of the ordinal scale of TripAdvisor. This inflation of positive ratings is in line with extant eWOM research (e.g., Mariani and Borghi, 2018; Sridhar and Srinivasan, 2012; Stamolampros et al., 2019). Regarding service robots' evaluation, 8.6% of ORs favourably mentioned this service attribute, while solely 1% of the overall sample left a negative statement. Aware that these low percentages could potentially undermine the reliability of the estimation results, we conducted a robustness check on a balanced sample (see **Section 4.4.3.1**). Besides, due to the high skewness of the distribution of *Reviewer Contribution* and *Review Length*, we included in the model their logarithmic transformation. Further, examining the correlation among key predictors (see **Table 15**), none of the values indicates strong correlation (absolute value higher than 0.7, see Ratner, 2009), providing evidence against multicollinearity issues.

__Table 13__. Variables description econometric models customer satisfaction

Variable	Description
Dependent Variable	
Overall Review Rating	It is the rating score provided by the online reviewer (ranging from 1 to 5) which captures her overall level of satisfaction with the service experience (e.g., Chen et al., 2018).
Focal Independent Variables	
Robot Pos	It is a dummy variable equal to 1 if the online reviewer has provided a statement related to the service robot which is associated with a positive sentiment polarity score. It is equal to zero otherwise.
Robot Neg	It is a dummy variable equal to 1 if the online reviewer has provided a statement related to the service robot which is associated with a negative sentiment polarity score. It is equal to zero otherwise.
Platform Controls	
Observed average Rating	It represents the rating observed by the online reviewer on TripAdvisor before submitting her review.
Submission Device	It represents the device used by the online reviewer to submit her OR. In particular, it is equal to 1 if the reviewer has used a mobile device, and zero if desktop.
Reviewers Controls	
Reviewer Contribution	It denotes the number of reviews posted on TripAdvisor by the reviewer.
No Identity Disclosure	It is a dummy variable equal to 1 if the reviewer has not agreed to share either her age or her gender, 0 otherwise. (see Gao et al., 2018)
Travel Type	It is a categorical variable which is associated to 5 possible travel types: Business, Solo, with Family, with Friends and as a Couple.
Text analytics Controls	
Overall Sentiment Polarity	It is a continuous variable ranging from -1 (extremely negative) to +1 (extremely positive) which contains the sentiment polarity score associated to the entire text of the OR (Hutto and Gilbert, 2014).
Review Length	It denotes the number of words embedded in the OR.
Temporal controls	
Year	It is a numeric variable which identifies the year when the OR was originally submitted. In the model it has been operationalized as a set of dummy variables (one for each year except for the first year of observations).
Hotel Controls	

Hotel ID	It denotes a identifier that is unique to each hotel in the dataset.
Chain	It is a dummy variable that assumes the value of 1 when the hotel belongs to a chain and zero otherwise.
Hotel Star Rating	It refers to a categorical variable ranging from 1 to 5 which classifies hotels based on their category.

Table 14. *Descriptive statistics*

	Mean/Proportion	SD	Min	Max
Review Rating	4.288	1.006	1.000	5.000
Robot Pos	8.6%		0.000	1.000
Robot Neg	1.0%		0.000	1.000
Observed Average Rating	4.320	0.188	3.000	5.000
Log(Reviewer Contribution)	2.316	1.944	0.000	11.703
No Identity Disclosure	69.8%		0.000	1.000
Overall Sentiment Polarity	0.787	0.414	-0.996	1.000
Log (Review Length)	4.385	0.695	2.079	7.610
Mobile Submission	28.6%		0.000	1.000
Chain	94.0%		0.000	1.000
Observations	32,985			

Table 15. *Correlation Table*

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Review Rating	1							
(2)	Robot Pos	0.0536***	1						
(3)	Robot Neg	-0.0579***	-0.0304***	1					
(4)	Observed Average Rating	0.158***	-0.0230***	-0.0501***	1				
(5)	No Identity Disclosure	0.0247***	-0.0318***	-0.0314***	0.0406***	1			
(6)	Log(Reviewer Contribution)	-0.0571***	0.0581***	0.0367***	-0.0710***	-0.490***	1		
(7)	Mobile Submission	0.00306	-0.00477	-0.0118*	0.0655***	0.0266***	0.192***	1	
(8)	Overall Sentiment Polarity	0.579***	0.0923***	-0.0574***	0.0767***	-0.0464***	0.0400***	0.0154**	1
(9)	Log (Review Length)	-0.214***	0.111***	0.0940***	-0.0103	-0.234***	0.313***	-0.00102	-0.00296

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4 Findings

4.4.1 Main findings

The empirical results of the study are unveiled in **Table 16**, where the econometric coefficients of the model specification described in **Equation 1** are presented. As clear from Model 1, *Robot Pos* shows a positive and statistically significant coefficient ($\beta_1 = 0.273$, p<0.001). Therefore, as expected in HP1, a positive performance stemming from a service robot interaction increases the chances of online reviewers posting higher review ratings, which translates into higher overall customer satisfaction. On the contrary, *Robot Neg* displays a negative but not significant coefficient ($\beta_2 = -0.0183$, n.s.), supporting HP2. In other words, the presence of a negative performance associated with a robotics service encounter does not significantly alter the overall satisfaction level of a guest. To a certain extent, it can be argued that, despite being reported, robotic service failure is not taken into account in the mental process undertaken by consumers in the post-encounter stage to generate their rating scores. Taken together, these findings, combined with the classification schema developed by Lin et al. (2010), suggest that service robot is an "excitement factor", and corroborate the idea that service robots are able to act in the satisfaction domain positively surprising guests while they do not significantly lead to dissatisfaction with the hospitality service when the performance falls below expectations. Overall, this supports the main research proposition of the study.

Referring to the effects of the control variables embedded in Model 1, their coefficients confirm the findings of extant empirical literature in marketing and tourism marketing management. For instance, review ratings are positively and significantly influenced by previous ratings (Sridhar and Srinivasan, 2012) and the overall sentiment of the review content (Geetha et al., 2017). Conversely, the reviewer level of contribution and length of OR exert a negative and significant effect on the review rating as well as business travelers (Gao et al., 2018; Godes and Silva, 2012). Moreover, identity disclosure does not impact the reviewers' evaluation (Sridhar and Srinivasan, 2012).

Investigating the robustness of the main findings, Model 2 in **Table 16** reports the results obtained by estimating the econometric model in the sample reporting solely ORs written in English. The outcomes are in line with the ones of Model 1, corroborating the abovementioned effects.

***Table 16**. Estimation results Ordered logistic models – Dependent Variable: Overall Review Rating*

		Model (1) Full Controls	Model (2) English Sample
Robot Pos	**H1**	0.273***	0.260***
		(0.0428)	(0.0469)
Robot Neg	**H2**	-0.0183	-0.107
		(0.110)	(0.130)
Observed Average Rating		1.028***	1.074***
		(0.177)	(0.190)
No Identity Disclosure		-0.000160	0.00257
		(0.0283)	(0.0327)
Log (Reviewer Contribution)		-0.0957***	-0.0878***
		(0.00742)	(0.00847)
Mobile Submission		-0.0514	-0.0666*
		(0.0278)	(0.0320)
Traveled on business		-0.336***	-0.351***
		(0.0323)	(0.0351)
Traveled solo		0.111*	0.0964
		(0.0464)	(0.0509)
Traveled with family		-0.0728*	-0.0725*
		(0.0313)	(0.0353)
Traveled with friends		-0.0400	-0.0702
		(0.0417)	(0.0479)
Overall Sentiment Polarity		2.640***	2.696***
		(0.0315)	(0.0350)
Review Length		-0.703***	-0.737***
		(0.0182)	(0.0207)
Further Controls:			
Year Dummies		YES	YES
Chain		YES	YES
Star Rating		YES	YES
Hotel ID		YES	YES
Intercept-1		-1.330	-1.131
		(0.805)	(0.864)
Intercept-2		-0.220	-0.00503
		(0.805)	(0.864)
Intercept-3		1.164	1.348
		(0.805)	(0.864)
Intercept-4		3.153***	3.247***
		(0.805)	(0.864)
Observations		32,976	26,453
Pseudo R^2		0.169	0.173
AIC		62,475.8	50,173.9
LR Chi2		12,633.6***	10,461.8***
Log Likelihood		-31,170.9	-25,019.9

Notes: Standard errors in parentheses. Model 1 has slightly less observations than the final sample described in **Section 4.3.1** (N=32,985) since 9 hotels in the sample started their operations with service robots already in their workforce. Thus, the first reviewer of these companies did not observe any prior rating. As such, the dimension "Observed Average Rating" is missing. We did not deploy any imputation technique due to the very small number of observations (9). Model 2 contains only ORs written in English.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.2 Robustness Check: Service Quality

In light of the fact that TripAdvisor allows reviewing guests to provide the scores related to different service attributes (such as Room, Cleanliness, Value, Service Quality, Sleep Quality, and Location) we performed the first set of robustness checks using *Service Quality* as the dependent variable. Theoretically, the concept of customer satisfaction slightly differs from that of service quality. As highlighted in the seminal work of Parasuraman et al. (1988) within the service marketing research domain, satisfaction has a transaction-specific nature (Oliver, 1981), whereas perceived service quality "*is a global judgment, or attitude, relating to the superiority of the service*" (Parasuraman et al., 1988: p. 16). This definition confers a relatively more stable nature to the construct of service quality. Nonetheless, the two concepts are undoubtedly intertwined. Indeed, transaction-specific satisfaction ratings are the ones involved in the dynamic process that establishes service quality (Boulding et al., 1993). As simply put by Oliver (1981): "*satisfaction soon decays into one's overall attitude toward purchasing products*". Yet, it is service quality that ultimately impacts repurchase intentions (Wirtz and Lovelock, 2018).

Thus, we re-ran the entire set of models presented in **Table 16** to assess whether the evaluation of service robots had the capability to influence more stable consumers' beliefs operationalize through service quality ratings (see **Table 17**). As such, we implicitly proxied service quality with the service quality score provided by the reviewing guests, assuming that that score was associated with consumers' judgments of service quality. Remarkably, all the models (Models 3 and 4) present results in line with the findings previously highlighted in **Section 4.4.1**. This not only corroborates the main findings of the manuscript but also makes them even stronger since service quality is a long-lasting belief rooted in consumers' minds. However, as illustrated in the next section, due to other potential reliability concerns, we performed a second set of robustness checks.

***Table 17**. Estimation results Ordered logistic models – Dependent Variable: Service Quality Rating*

		Model (3) Full Sample	Model (4) English Sample
Robot Pos	**H1**	0.260***	0.269***
		(0.0533)	(0.0587)
Robot Neg	**H2**	-0.110	-0.150
		(0.133)	(0.157)
Observed Average Rating		0.541*	0.407
		(0.244)	(0.256)
No Identity Disclosure		0.0458	0.0465
		(0.0362)	(0.0419)
Log (Reviewer Contribution)		-0.0682***	-0.0557***
		(0.00978)	(0.0111)
Traveled on business		-0.152***	-0.184***
		(0.0403)	(0.0434)
Traveled solo		0.0749	0.00789
		(0.0581)	(0.0631)
Traveled with family		-0.0357	-0.0476
		(0.0391)	(0.0440)
Traveled with friends		-0.0589	-0.120*
		(0.0532)	(0.0606)
Overall Sentiment Polarity		2.239***	2.244***
		(0.0368)	(0.0397)
Review Length		-0.510***	-0.578***
		(0.0227)	(0.0257)
Further Controls:			
Year Dummies		YES	YES
Chain		YES	YES
Star Rating		YES	YES
Hotel ID		YES	YES
Intercept-1		-2.203*	-2.909**
		(1.067)	(1.117)
Intercept-2		-1.336	-2.069*
		(1.066)	(1.117)
Intercept-3		-0.0464	-0.857
		(1.066)	(1.117)
Intercept-4		1.611	0.729
		(1.067)	(1.117)
Observations		20,903	17,518
Pseudo R^2		0.126	0.134
AIC		40,857.9	33,393.4
LR Chi2		5,895.8***	5,148.4***
Log Likelihood		-20,363.0	-16,630.7

Notes: Standard errors in parentheses. The number of observations is lower than the models presented in **Table 16** since the Service Score is not a mandatory feature, thus, it presents a series of missing values in the overall sample. Model 4 contains only ORs written in English. The mobile submission variable is not included in the models since the TripAdvisor mobile app does not allow reviewers to rate "Service Quality".
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.3 Robustness Check: Propensity Score Matching

4.4.3.1 Deployment of Propensity Score Matching

The approach used so far to test the relationship between the introduction of service robots and customer satisfaction could have been prone to endogeneity issues, mainly related to sample selection (Cameron and Trivedi, 2005). Indeed, individual characteristics could influence whether the tourist decides to interact with service robots (Ivanov et al., 2019a). Besides, data sparsity could also be seen as a potential bias, influencing the main findings of the study (Bi et al., 2020). This is clearly displayed in the OR data used in this work since only 12.17% of the ORs in the entire sample report a statement referring to service robots (N=4,013). Accordingly, due to the relatively low frequency of negative comments related to service robots, the econometric results might present a spurious association between *Robot Neg* and customer satisfaction.

To reduce the abovementioned biases, we chose to leverage on *propensity score matching,* a quasi-experimental analysis. This technique allows researchers to analyse the results related to an outcome variable among individuals who had – a priori – an analogous probability to engage in the behaviour under examination (Rosenbaum and Rubin, 1983). Originated by the seminal work of Rosenbaum and Rubin (1983), it has gradually become a popular matching technique in a wide range of research fields (Caliendo and Kopeining, 2008) including tourism and hospitality (Yang et al., 2019). Besides, it has also been used to enhance causal interpretations to research findings (Driffield et al., 2016). Essentially, through this matching exercise, we aimed to associate each reviewer reporting service robots with the closest reviewer not mentioning this attribute but being the most similar based on a set of predefined characteristics. This allowed us to balance the sample in terms of: 1) volumes, so that half of the sample mentions service robots (thus reducing data sparsity concerns); 2) individual characteristics, thereby diminishing sample selection issues. More specifically, we matched each of the 4,013 ORs containing a portion of text related to service robots with a counterpart OR non mentioning this service element. This led us to obtain a sample of 8,026 ORs after having performed this matching exercise.

The first step to deploy propensity score matching was related to the estimation of the propensity score (Caliendo and Kopeinig, 2008), which is considered a crucial step in the analysis (Driffield et al., 2016). As such, to calculate the propensity score of reporting service robots we estimated a logistic regression model having as dependent variable a dummy variable equal to 1 if the reviewer has reported service robots in her OR and 0 otherwise. As independent variables, we used a set of covariates that have been conceptualized or empirically tested in extant literature as having an impact on the adoption of service robots or reviewing behaviours (Forman et al., 2008; Ivanov et al., 2018a; 2018b; Mariani et al., 2019; Tung and Au, 2018; Xiao and Kumar, 2019). In particular, at the reviewer level, we exploited features such as travel type (Tung and Au, 2018), reviewer experience (Ivanov et al., 2018a), submission device (Mariani et al., 2019) and identity disclosure (Forman et al., 2008). Further, we introduced in the model the set of hotel controls used in the main econometric estimation, namely *Chain*, *Star Rating*, and *Hotel ID* since firm characteristics can impact the degree of robotics adaptation (Xiao and Kumar, 2019). Finally, we added a time-related variable, labelled "*months_from_intro*" to account for potential organizational learning mechanisms that could have led the organization to adjust, improve or change the tasks associated with the service robot (Levitt and March, 1988). Overall, this is a parsimonious set of features in order to avoid any over-parametrization issue in the estimation of the propensity score (Bryson et al., 2002). Nonetheless, as suggested by extant literature revolving around service robotics (see, Ivanov et al., 2018a; Wirtz et al., 2018), also demographic characteristics, such as gender, age and nationality can affect the propensity to engage in human-robot interactions. However, due to the high number of missing values associated with these metrics in the research sample, we decided not to use this set of features in this study.

Second, in line with Yang et al. (2019), we opted for the nearest neighbour algorithm to select the matching observations among reviewers not reporting service robots. Third, to verify the assumption of common support, we examined the density distribution functions of the treated and control groups in the overall population (Caliendo and Kopeinig, 2008). Finally, based on the newly obtained sample we re-ran all the econometric analyses.

4.4.3.2 Propensity Score Matching results

Regarding the robustness check through propensity score matching, before evaluating the econometric results, we conducted a series of analyses to ensure the quality and reliability of the matching. To this aim, we first inspected the common region assumption, visually assessing the density distributions of the propensity score for the sample of reviewers writing about service robots vis-a-vis reviewers not mentioning this aspect (Caliendo and Kopeinig, 2008). As clear from **Figure 18**, there seems to be a reasonable overlap between the areas underneath the two functions, indicating that the current analysis does not suffer from common support issues. Besides, after having performed the matching, we checked the balance of every covariate used to calculate the propensity indicator. **Table 18** shows how all the differences in terms of standardized mean are close to zero, whereas all the variance ratios present values close to one. Moreover, for the overall sample, we calculated the Rubin's B and the Rubin's R indicators (Rubin, 2001), which equated 12.73 and 1.31, respectively: these values perfectly fit the intervals recommended by Rubin (2001) for considering the sample sufficiently balanced. Taken together, these results certify the quality of the performed matching, ensuring that each reviewer mentioning service robots was associated with the most similar reviewer not mentioning service robots.

As far as the econometric results are concerned, **Table 19** displays the entire set of models estimated using the overall review rating (Models 5 and 7) and the service quality rating (Models

6 and 8) as dependent variables, in both the entire (Models 5 and 6) and English (Models 7 and 8) samples. Interestingly, the main findings of the study still hold in this semi-experimental configuration. Indeed, as depicted in **Table 19**, the coefficient of *Robot Pos* is positive and statistically significant in all the estimated models, confirming HP1. Conversely, *Robot Neg*, despite presenting a negative coefficient, is never found to be statistically significant, in line with HP2. Therefore, this further empirical validation provides important evidence in favour of an apparently causal relationship rather than a spurious association between service robots and customer satisfaction.

Table 18. *Descriptive statistics related to the quality of the matching performed*

Covariate	**Standardized Mean Differences**	**Variance Ratio**
No Identity Disclosure	0.00199	0.9982
Log (Reviewer Contribution)	0.059	0.9068
Mobile Submission	0.01196	1.027
Traveled on business	0.00199	1.0072
Traveled solo	-0.00199	0.9715
Traveled with family	0.01072	1.0158
Traveled with friends	-0.00274	0.969
Months from Intro	-0.179	1.0045

Figure 18. *Density distributions of the propensity score for the sample of reviewers mentioning service robots vis-à-vis reviewers not mentioning it.*

Table 19. *Econometric Results Propensity Score Matching sample*

		Model (5) Total Review Score	Model (6) Total Service Score	Model (7) English Review Score	Model (8) English Service Score
Robot Pos	**H1**	0.269***	0.342***	0.290***	0.357***
		(0.0503)	(0.0631)	(0.0546)	(0.0695)
Robot Neg	**H2**	-0.181	-0.163	-0.229	-0.196
		(0.115)	(0.140)	(0.143)	(0.165)
Observed Average Rating		0.438	1.445**	0.968**	1.538***
		(0.301)	(0.444)	(0.332)	(0.454)
No Identity Disclosure		-0.0231	0.0440	-0.0450	0.00855
		(0.0549)	(0.0709)	(0.0627)	(0.0801)
Log (Reviewer Contribution)		-0.0893***	-0.0683***	-0.106***	-0.0861***
		(0.0145)	(0.0192)	(0.0161)	(0.0212)
Mobile Submission		0.121*		0.124	
		(0.0559)		(0.0652)	
Traveled on business		-0.436***	-0.333***	-0.431***	-0.370***
		(0.0708)	(0.0886)	(0.0757)	(0.0923)
Traveled solo		0.100	0.0943	0.0714	0.00263
		(0.0975)	(0.121)	(0.103)	(0.130)
Traveled with family		-0.192**	-0.0932	-0.269***	-0.178*
		(0.0601)	(0.0755)	(0.0685)	(0.0840)
Traveled with friends		-0.244**	-0.108	-0.228*	-0.221
		(0.0827)	(0.106)	(0.0944)	(0.119)
Overall Sentiment Polarity		2.489***	2.005***	2.635***	2.121***
		(0.0697)	(0.0824)	(0.0917)	(0.0921)
Review Length		-0.577***	-0.512***	-0.594***	-0.586***
		(0.0355)	(0.0440)	(0.0415)	(0.0499)
Further Controls:					
Year Dummies		YES	YES	YES	YES
Chain		YES	YES	YES	YES
Star Rating		YES	YES	YES	YES
Hotel ID		YES	YES	YES	YES
Intercept-1		-4.558**	-0.594	-2.003	0.151
		(1.385)	(2.018)	(1.543)	(2.060)
Intercept-2		-3.201*	0.392	-0.693	1.035
		(1.384)	(2.017)	(1.542)	(2.060)
Intercept-3		-1.597	1.892	0.829	2.546
		(1.384)	(2.017)	(1.541)	(2.060)
Intercept-4		0.480	3.611	2.788	4.172*
		(1.384)	(2.018)	(1.542)	(2.061)
Observations		8,019	5,264	6,661	4,396
Pseudo R^2		0.151	0.129	0.150	0.142
AIC		15,305.3	10,279.1	12,621.4	8,171.4
LR Chi2		2,693.9***	1,502.0***	1,681.5***	1,326.1***
Log Likelihood		-7,586.6	-5,075.6	-6,245.7	-4,020.7

Notes: Standard errors in parentheses. Model 5 has slightly less observations than the final sample described in **Section 4.3.1** (N=8,026) since 7 online reviewers did not observed any prior rating. As such, the dimension "Observed Average Rating" is missing. We did not deploy any imputation technique due to the very small number of observations (7). The mobile submission variable is not included in models 6 and 8 since the TripAdvisor mobile app does not allow reviewers to rate "Service Quality". * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.5. Discussion

4.5.1 Theoretical Implications

This study contributes to different streams of literature lying at the intersection of the evaluation of the service experience, human-robot interaction, eWOM, and operations management.

First, to the best of our knowledge, it constitutes the first attempt to analyse the existence of an asymmetrical relationship between service robots and overall customer satisfaction, proxied by OR ratings. As such, it answers the call for empirical studies related to the impact of service robotics in tourism (Ivanov et al., 2019; Tussyadiah, 2020). More specifically, it aims to bridge the gap in extant literature related to the understanding – in the post-service consumption phase – of the effect of service robots on overall customers judgements in terms of satisfaction and quality with the service experience (Lu et al., 2020). Following the progress in the customer satisfaction literature in the tourism and hospitality domain, the three-factor framework of customer satisfaction is used for its superior explanatory power (e.g., Bi et al., 2020). The results, stemming from mechanisms belonging to the service innovation and attribution theory applied to the human-robot interaction, strongly highlight how positive performance associated with the interaction of service robots outweighs the effect of negative performance in relation to overall customer satisfaction and service quality. Hence, on the one hand, it empirically validates conceptual and qualitative studies that suggest that service robots generate delight for service customers (Ivanov and Webster, 2019a; Stock and Merkle, 2018; Tung and Au, 2018). In turn, it confirms insights stemming from the service (e.g., Evangelista and Vezzani, 2010) and tourism and hospitality innovation literature (e.g., Martin-Rios and Ciobanu, 2019). On the other hand, service robots seem to not significantly act in the dissatisfaction domain, possibly reflecting the results obtained by researchers investigating the attribution of responsibility during robotic service failures (Jörling et al., 2019; Fan et al., 2020). This implies that, even in presence of a negative performance stemming from a robotic service encounter, this event does not significantly impact the overall satisfaction of the guest with the service experience, suggesting that service robots evaluation falls in the consumers' "*zone of tolerance*". These results, to a certain extent, are at odds with what has been proposed by Xu et al. (2020a), who predicted potential service quality pitfalls when introducing service robots in hotels' operations. As clear from the study's findings, the potentially low variability associated with the introduction of service robots in hotels' processes is outweighed by their novelty effect, which makes them an excitement factor in the consumers' eyes.

Second, distinctively from other empirical studies leveraging on survey and laboratory experiment data (i.e., Fan et al., 2020; Jörling et al., 2019; Tussyadiah and Park, 2018), this work exploits OR data on a very large sample of international hotels (perhaps the largest considered so far), adding to the nascent field employing eWOM to explain travellers' perceptions of service robots (Borghi and Mariani, 2020; Gretzel and Murphy, 2019; Tung and Au, 2018). In particular, it extends the novel concept of *online robotic discourse* proposed by Borghi and Mariani (2020) to derive the levels of performance perceived by the reviewing guest when evaluating service robots. Without leveraging on *online robotic discourse* and related analytics we would have not been able to obtain such a rich dataset for our analyses. As such, this study showcases not only the importance of *online robotic discourse*, as suggested by Borghi and Mariani (2020), but also how metrics extracted from it can be effectively used to test hypothesised relationships stemming from the analysis of extant literature.

Third, as we found that negative evaluations of service robots do not significantly affect customer satisfaction and the overall perceived service quality, there seems to be no supporting evidence of the existence of a self-serving bias. This extends the results of Fan et al. (2020) and Jörling et al. (2019) to the overall evaluation of the service experience. In line with Fan et al. (2020), this could be explained by the fact that the social cues embedded in service robots induce self-blame that in its turn alleviates the dissatisfaction with a negative performance from a human-robot interaction. This claim theoretically corroborates existing scholarly definitions of service robots in service marketing (Jörling et al., 2019; van Doorne et al., 2017) that depict robots as social agents. More broadly, this would support arguments in favour of alternative approaches in the sociomateriality literature that challenge the conventional separation between the social and the material spheres (see Orlikowski, 2007). Indeed, as stressed by Latour (2005), agency is not to be considered an innate human characteristic, but a capacity, relational in nature, that is obtained by associating a set of entities (either human or non-human). Therefore, combining Latour thinking with the principles of the service-dominant logic proposed by Vargo and Lusch (2004; 2008), the social (people) and the material (technologies) can be perceived as equal actors whose interaction has the capability to co-create value. Based on this theoretical ground, the current study contributes to the human-robot interaction literature assessing empirically how the interaction between service customers and service robots effectively creates value in the hotel market (which is reflected in higher OR ratings).

Fourth, evaluating the three-factor theory through a managerial lens, following the classification schema developed by Matzler and Hinterhuber (1998), the study’s results highlight how service robots can *effectively* be associated with differentiation strategies (Porter, 1985). Thus, this finding quantitatively corroborates the qualitative results of Tuomi et al. (2020b) who, based on observation of businesses and interviews with tourism and hospitality managers, found that service robots were used mainly to pursue novel differentiation strategies. Yet, this also makes an important contribution to the literature at the intersection of operations management and service marketing. Indeed, combing the study’s findings with the claim of Rust and Huang (2012) who predict an increase of productivity related to the introduction of automation, we can argue that service robots can be seen as a means to conjointly achieve gains in customer experience, service quality and productivity. This would mean that the introduction of service robots does not generate necessarily a trade-off between productivity and satisfaction (Rust and Huang, 2012), but rather allows hotels to achieve *cost-effective service excellence*, namely service excellence at low unit costs (Wirtz and Zeithaml, 2018).

4.5.2 Practical Implications

Starting from a micro-level of analysis, this study provides clear evidence of a positive influence of service robots in the evaluation of the overall hotel customer experience, encouraging the adoption of this form of innovation by hotel managers. Negative performances related to service robots' interactions exist, but they do not significantly influence the overall travellers' judgements. This confirms the view of Kuo et al. (2017), who highlights how service robots are an important resource able to sustain hotel competitiveness. However, managers should carefully evaluate the fit of this source of innovation into their current brand image and operations (Kuo et al., 2017). Furthermore, as depicted by Xu et al. (2020a), it is of paramount importance for businesses to proactively collect and analyse customers' feedback on service robots to gain a better understanding of the guest levels of satisfaction with them. Among the plethora of possible data sources, social media seems to be a critical means to promote and track the evolution of service robot's evaluation (de Kervenoael et al., 2020). Thus, as far as we know, this is the first study specifically developing an analytical strategy to control the impact of service robots in hotels' operations. As such, the innovative methodology deployed in the manuscript could be leveraged by hotel operations managers to assess and monitor - in real-time - the performance of service robots with respect to online evaluations of the overall service experience.

As far as a meso-level of analysis is concerned, the novelty effect associated with service robots could decay in the medium and long term, making them increasingly perceived as either a basic or performance attribute in hotel's operations. Put it simply, in the future, like the well-known example of ATMs, service robots could become a commodity in the hotel industry, more affordable and easier to embed in the hotel's strategy (Wirtz et al., 2018). Thus, hoteliers adopting service robots should carefully think about the unique traits characterizing their robotic service offering and constantly improve them following an incremental innovation trajectory. This would make hotel managers able to maintain their competitive positions in the hotel market, as well as continuously delight their customers leveraging on service robotics. As an example, after one year of having introduced robot butlers in their operations, the Hotel EMC2 in Chicago decided to create a specific menu that is exclusively delivered by their service robots. This not only made service robots more popular among hotel guests but also boosted the number of in-room dining deliveries, almost doubling them (Escobar, 2018). Moving to Asia, the YOTEL Singapore in Orchard Road, recent winner of the "Robotics Award for hospitality and leisure" in the city (Singapore Business Review, 2019), has uniquely tailored the interactions with its two service robots, Yoshi and Yolanda. The robots resemble the brand in their design, but each of them is equipped with a distinctive dictionary of phrases that aims to portray different personalities and make them being perceived as social agents able to deliver a memorable customer experience. Due to their service robots increased popularity, YOTEL Singapore Orchard Road has recently introduced the new concept of ROBO-CATION, an exclusive robot-centric holiday package where the consumer experience entirely revolves around human-robot interaction (YOTEL Singapore, 2020). Despite being remarkable examples of the deployment of service robots, the latter perfectly fit the company philosophy, "*At the intersection of art & science*" for EMC2, and "*Constant and Never-Ending Innovation*" for YOTEL.

Referring to a macro level, although these results incentivise the global adoption of service robots in the hotel market, they can also exacerbate the debate about societal issues stemming from their introduction. For instance, global leaders are demanding the establishment of "*robot taxes*" (Davenport, 2019). This is due to the fact that in the global economy the main source of taxation is referred to human workers' wages (Webster and Ivanov, 2020). If service robots were to substitute human employees, governments should create completely new taxation systems, which could include robot taxes. Besides, discussion related to employment challenges (Huang and Rust, 2018; Tussyadiah, 2020) especially concerning to the decency and sustainability of work conditions (Tuomi et al., 2020a) will soon follow. As highlighted by Guerreiro et al. (2019) if governments and policymakers do not step in the debate, the gradual decrease of automation costs will translate into a wider discrepancy in income inequality. Despite controversial positions in this regard (see, Wirtz et al., 2018), we do not truly know whether the disruption brought about by artificial intelligence infused in service robots will follow the same pathway of the previous industrial revolutions, generating wealth and new areas of employment. As such, in this climate of uncertainty, policymakers are called to timely act and actively support the transition to a more automated service economy, avoiding being caught unprepared when the global adoption rate will surge dramatically.

Lastly, the manuscript bears practical implications related to its impact on the current COVID-19 pandemic. Since service robots have been found to have a largely positive relationship with respect to customer satisfaction and perceived overall service quality, this ensures that, even in a high-touch service context, high-tech can significantly enhance the consumer experience. Thus, in light of the social distancing measures put in place in many countries around the world, service robots could act as a pivotal element in restructuring strategies to respond to the unprecedented challenges brought about by the COVID-19 pandemic in the hotel industry (Zeng et al., 2020). In fact, the deployment of service robots can guarantee a high level of cleanliness and limit human-to-human interactions, which could ultimately decrease the risk perceived by travellers in booking their hotel stays (Jiang and Wen, 2020). For instance, some hotels in the United States have started to deploy cleaning robots designed for the healthcare industry to sanitise their rooms (Qubein, 2020), whereas, Chinese hotels have introduced delivery robots to provide non-contact food service to guests' spending their quarantine period in the hotel facilities (Cuthbertson, 2020). Despite some of these robots being already in use in some service companies before the global pandemic, the global demand is expected to dramatically increase in the foreseeable future due to the ongoing pandemic (Financial Times, 2020).

4.6 Conclusions, Limitations and Future Research

Drawing upon the three-factor theory of customer satisfaction applied to electronic Word-Of-Mouth data, this study aims to determine to what extent service robots affect overall customer satisfaction, under the guise of online review ratings. To this end, a penalty-reward contrast analysis built upon text analytics techniques is performed on a sample of almost 70,000 TripAdvisor ORs covering 44 international hotels embedding service robots in their operations.

The results show that positive performance associated with service robots positively and significantly influences customer satisfaction, whereas negative performance does not significantly alter customer satisfaction. Overall, these findings suggest that service robots constitute an "excitement factor" (or satisfier) in the three-factor framework of customer satisfaction. Hence, service robots are found to act in the satisfaction domain, but do not seem to significantly cause dissatisfaction when performance falls below expectations.

Despite contributing to the extant literature, this study presents some limitations that could be addressed by future research in the field. First, the findings could be biased due to the specific moment in time when data was collected. Indeed, in the tourism and hospitality setting, service robots have only recently been introduced in business operations and their effect on customer satisfaction could change over time when consumers will be less prone to accept robotics service failures. Future research, adopting a longitudinal perspective with a longer time span, could shed light on the moment where the transition from being an "excitement factor" to a "performance factor" happens. Besides, scholars could be interested in exploring whether business characteristics are able to fuel the "excitement factor" trajectory even longer. Second, despite using a sample of 44 international hotels, we only collected data from one OR platform, namely TripAdvisor. To guarantee the generalization of the results, researchers could extend the current research design embedding data from other reviewing platforms (i.e., Booking.com or Yelp). Third, even though different robustness checks have been performed to rule out possible problems related to sample characteristics and data sparsity, endogeneity could still be an issue. Indeed, reviewers' demographic characteristics, such as nationality, age, and gender, could have the power to influence the acceptance of service robots (see Ivanov et al., 2019). TripAdvisor optionally allows reviewers to disclose their age and gender, but unfortunately in the analysed sample less than 30% of the overall population of ORs presents this information; thereby, we decided not to use these metrics in the empirical analysis. Controlling for these dimensions and possibly conducting field experiments (Viglia and Dolnicar, 2020) would ultimately validate the study's findings. Fourth, the sample obtained reflects the current hotels' adoption of service robots and includes mostly robot butlers. This could undermine the generalisation of the study's results. In this regard, future researchers, leveraging on a more balanced sample, could investigate whether differences in perceptions exist in relation to different types of robots. Besides, evaluations of service robots could be analysed referring to specific travel motives to provide precise advice in terms of whom to target when promoting service robots. Finally, building on the reported findings, future researchers could examine whether and how factors at the firm, service robot, or reviewer level could act as moderators or mediators in the relationship between service robots and customer satisfaction.

Chapter 5: Conclusions

This last and final chapter of my PhD thesis comprises an overview of the body of knowledge created through the core chapters of the thesis (**Chapters 2**, **3**, and **4**), highlighting the theoretical and methodological contributions, practical implications, limitations, and providing a research agenda for future scholars.

5.1 General conclusions

The entire PhD thesis revolves around the 4th Industrial Revolution, a socio-technical process able to disrupt entire industries and our society as a whole. Due to its unprecedented transformative nature, management and social sciences scholars have recently started examining the phenomenon. Nonetheless, the structure of this emerging research stream has never been depicted nor critically analysed. To bridge this gap, the first part of **Chapter 2** aims to answer the following research question: *what is the intellectual structure of recent/emerging managerial and social sciences literature related to Industry 4.0?* It does so, using a systematic quantitative literature review, combined with the application of network analysis and bibliographical coupling techniques based on a data-driven approach. The results show that the scientific outputs can be grouped into seven communities. The latter belong to three main research streams: advanced manufacturing technologies, Industry 4.0 technologies, and additive manufacturing. Moreover, the core themes of the clusters identified can be linked to form the overarching framework present in **Figure 13**, which can be used as a reference point for future managerial research aiming to explore the new industrial revolution. However, as clear from the results, scholarly investigations are still mainly related to the manufacturing domain and focus on the ancestral label of the revolution, namely Industry 4.0. Conversely, business leaders are increasingly emphasising the importance of services and, in turn, the service industries in the 4th Industrial Revolution (European Commission, 2016a; German Federal Ministry, 2017; Rehse et al., 2016). Nevertheless, despite services being part of the rhetoric in a wide range of industrial governmental plans, they have never been critically assessed from a managerial point of view. As such, the second part of **Chapter 2** answers this research question: *how and to what extent are management scholars addressing the Industry 4.0 phenomenon in the service industries?* By means of a quantitative and qualitative examination of the full text of studies retrieved through the abovementioned systematic quantitative literature review, services and more broadly the service industries appear an unexplored component of the 4th Industrial Revolution. However, a future service orientation coupled with a more customer-centric view is expected by scholars in management since services can play a remarkable role in capturing the entire value created by the deployment of Industry 4.0 initiatives. As such, future scholarly efforts should be directed toward the service industries.

In particular, within the literature pertaining to the digital transformation of services, one of the main sources of innovation is the gradual infusion of artificial intelligence in robots, a key technological pillar of Industry 4.0, that in the service domain is named service robots (Huang and Rust, 2020; Jörling et al., 2019). Being able to effectively interact with the service customer, they can potentially revolutionise the service experience, especially in a high-touch domain, such as the tourism and hospitality one, where it is historically difficult to efficiently innovate. However, extant literature lacks empirical evidence on the relevance and distinctiveness of this new form of innovation after the service consumption phase. For this reason, **Chapter 3** provides a preliminary answer to the research question: *are service robots becoming an increasingly distinctive and popular feature in hotel-related eWOM beyond their introduction?* Leveraging on research and theorisations pertaining to the application of electronic Word-Of-Mouth (eWOM) as a useful means to assess the introduction of innovative products or services in the marketplace, it develops the concept of *online robotic discourse*. This is defined as eWOM in online reviews mentioning explicitly service robots deployed in hospitality services and it is used to track the adoption and diffusion of service robots over time. Exploiting this novel concept, through a data science approach, the work examines the entire set of online reviews (ORs) posted on TripAdvisor after the deployment of service robots in 19 leading international hotels pioneering this form of innovation. The research findings show how service robots are gradually perceived as a popular and distinctive factor in guests' evaluations of their hotel stay. A multitude of consumers over time perceive service robots as an attribute worth to be mentioned referring to the service experience. Moreover, this dimension seems to be attached to peculiar and highly influential content in the online community. Due to the paramount importance of customer satisfaction in the tourism and hospitality research domain, it is crucial to gain more knowledge related to the performance of human-robot interaction for researchers and practitioners.

Building on **Chapter 3**, and exploiting the superior explanatory power of the three-factor framework of customer satisfaction, **Chapter 4** aims to fill this gap by answering the following research question: *to what extent do service robots influence perceived customer satisfaction in the hotel industry?* Capitalising on text analytics features extracted from *online robotic discourse*, a penalty-reward contrast analysis is performed on the entire population of TripAdvisor ORs collected for a sample of 44 international hotels introducing service robots in their operations. The results, stemming from mechanisms belonging to the service innovation literature and attribution theory applied to human-robot interaction, strongly highlight how positive performance associated with the interaction of service robots outweighs the effect of negative performance in relation to overall customer satisfaction and service quality. This finding suggests that service robots constitute an "excitement factor" (or satisfier) in the three-factor framework of customer satisfaction. Hence, service robots are found to act in the satisfaction domain but do not seem to significantly cause dissatisfaction when performance falls below expectations.

Therefore, companies should confidently embrace this new form of innovation to pursue differentiation strategies.

Overall, this thesis demonstrates that (**a**) the managerial and social sciences intellectual efforts related to Industry 4.0 can be effectively classified in seven distinctive communities (**Chapter 2**); however, (**b**) services and the service industries are an unexplored but valuable component of the Industry 4.0 phenomenon (**Chapter 2**); (**c**) within the service industries, service robots - one of the pillar technologies of Industry 4.0 - are perceived as a popular and distinctive attribute in guests' evaluation of the stay (**Chapter 3**); and (**d**) they are able to positively impact the customer experience and perceived service quality (**Chapter 4**). Taken together, these findings suggest that digital transformation, in the age of the 4th Industrial Revolution, does not only promise productivity gains in the manufacturing industries, but it also has the capability to improve the customer experience and perceived service quality within the service industries.

5.2 Theoretical contributions

This PhD thesis contributes in manifold ways to a wide range of streams in extant literature. In particular, **Chapter 2,** delving deeper in the managerial and social sciences literature related to the 4th Industrial Revolution, contributes to the literature in the field (e.g., Piccarozzi et al., 2018; Schneider, 2018) being the first study providing a clear image of the intellectual structure of this emerging research stream (see **Figure 12**). Indeed, leveraging on a data-driven approach, which is innovative and cannot be found in existing reviews, seven different communities have been identified, and their own peculiarities have been discussed. More precisely, there are three distinctive core areas in the structural image provided: the first one discusses advanced manufacturing technologies; the second one encompasses Industry 4.0 technologies; and the last one relates to additive manufacturing. Advanced manufacturing technologies act as enabling layer for the development of Industry 4.0 initiatives for which researchers are trying to understand how the adoption and interaction of the Industry 4.0 technologies (Rüßmann et al., 2015) can create value within firms. Among scholars in management, additive manufacturing has gained particular attention since this technological pillar can truly revolutionise the entire value chain (Berman, 2012). Furthermore, **Chapter 2** contributes to the managerial and social sciences literature in Industry 4.0 creating a conceptual framework linking together the recurrent themes belonging to the clusters found (see **Figure 13**). This can be seen as a more holistic and comprehensive representation of the phenomenon under investigations and can potentially guide future investigations in scholars interested in the revolution. Besides, **Chapter 2**, to the best of the authors' knowledge, is the first study critically evaluating how scholars in management are embedding services and service industries into Industry 4.0 narratives. This is a unique and remarkable contribution in light of the potential evolution of Industry 4.0 initiatives to services and the service industries (European Commission, 2016a; German Federal Ministry, 2017; Rehse et al., 2016). Yet, research on the service component of Industry 4.0 it still is at an embryonic phase: *servitization* strategies could potentially maximise the value captured by the deployment of Industry 4.0 initiatives (Müller et al., 2018a; Nagy et al., 2018; Yang et al., 2017; Frank et al., 2019). As such, intellectual efforts of management scholars should also be directed toward the service industries. In doing so, **Chapter 2** provides a set of theoretical lenses and emergent disciplinary fields that could be used as a fruitful theoretical ground for future studies.

As far as **Chapter 3** is concerned, it contributes to the nascent stream of literature at the intersection of eWOM and human-robot interaction (Gretzel and Murphy, 2019; Tung and Au, 2018). Distinctively from other empirical studies leveraging on survey and laboratory experiment data (Viglia and Dolnicar, 2020), it is the first study quantitatively examining online conversations pertaining to service robots. Indeed, building on research and theorizations belonging to the application of eWOM to the diffusion of innovation (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Godes and Silva, 2004; Liu, 2006) it develops the concept of *online robotic discourse*. This is defined as "*eWOM in online reviews mentioning explicitly service robots deployed in hospitality services*" that can be used to monitor the diffusion (Godes and Mayzlin, 2004) and adoption (Dellarocas et al., 2007) of service robots over time. Besides, **Chapter 3** empirically proves how service robots are increasingly perceived as a popular attribute on guests' evaluation of the stay, beyond a mere novelty effect (Roehrich, 2004). Moreover, ORs mentioning service robots portray unique characteristics in terms of quantitative, reputational, and textual evaluation features that make them distinctive in the OR platform. This supports the idea that service robots distinctively impact the tourist experience. Hence, a better understanding of *online robotic discourse* can aid future researchers to enhance scholarly knowledge pertaining to (1) the diffusion and adoption of innovation (Rogers, 2003) involving service robots; (2) the impact of human-robot interactions in tourism (Newell and Card, 1985; Tussyadiah, 2020).

Finally, **Chapter 4** contributes to different streams of literature lying at the intersection of the evaluation of the service experience, human-robot interaction, eWOM, and operations management. Indeed, it represents the first attempt to empirically assess the role of service robots in customer satisfaction. Finding a positive and significant association between a positive performance of service robots and perceived overall satisfaction, it empirically validates conceptual and qualitative studies that suggest that service robots generate delight for service customers (Ivanov and Webster, 2019; Stock and Merkle, 2018; Tung and Au, 2018). In turn, this confirms insights stemming from the service (e.g., Evangelista and Vezzani, 2010) and tourism and hospitality innovation literature (e.g., Martin-Rios and Ciobanu, 2019). However, since service robots seem not to act in the dissatisfaction domain, this can potentially extend the results obtained by researchers investigating the attribution of responsibility during robotic service failures (Jörling et al., 2019; Fan et al., 2020). Indeed, taken together, these findings fail to support the existence of a self-serving bias, in line with Jörling et al. (2019) and Fan et al. (2020). Thus, as argued by Fan et al. (2020) this could be due to the fact that service robots are perceived as social agents, as conceptually claimed by extant service marketing literature (Jörling et al., 2019; van Doorne et al., 2017). As such, the results in **Chapter 4** are in favour of alternative approaches in the sociomateriality literature claiming that the social (people) and the material (technologies) can be perceived as equal actors (see Latour, 2005; Orlikowski, 2007). This, combined with the service-dominant logic (Vargo and Lusch, 2004; 2008), makes **Chapter 4** contributing to the human-robot interaction literature assessing empirically how the interaction between service customers and service robots effectively creates value in the hotel market. Moreover, **Chapter 4** extends the conceptualisation of *online robotic discourse* (Borghi and Mariani, 2020) showing how analytics extracted from it can be effectively used for hypothesis testing purposes. This adds to the emerging stream employing eWOM to explain travellers' perceptions of service robots (Borghi and Mariani, 2020; Gretzel and Murphy, 2019; Tung and Au, 2018). Last, **Chapter 4** suggests that service robots are an effective means to pursue differentiation strategies (Porter, 1985), corroborating the qualitative results of other researchers (e.g., Tuomi et al., 2020b). However, in the literature at the intersection of operations management and services marketing, as reported by Rust and Huang (2012), the introduction of automation is predicted to increase productivity in the service industries. Thus, combining the results of **Chapter 4** with the claim of Rust and Huang (2012), it can be argued that service robots are a means to conjointly achieve gains in customer experience, service quality and productivity. This would mean that the introduction of service robots does not necessarily generate a trade-off between productivity and satisfaction (Rust and Huang, 2012), but rather allows hotels to achieve *cost-effective service excellence*, namely service excellence at low unit costs (Wirtz and Zeithaml, 2018).

5.3 Methodological contributions

Part of the novelty of the thesis is also related to the methodological approaches deployed. First, **Chapter 2** leverages on a data-driven approach, which is innovative and cannot be found in existing reviews dealing with the Industry 4.0 phenomenon from a social sciences and managerial perspectives (Piccarozzi et al., 2018; Schneider, 2018). In particular, we adopted a specific bibliometric technique, namely *bibliographical coupling*, able to identify emerging research fields and streams in the relevant literature (Zupic and Čater, 2015). Furthermore, we carry out a more granular analysis leveraging a wider set of keywords and provide a clear visualization of the thematic clusters of the literature by applying a community discovery algorithm to the results of the bibliometric technique adopted. Combining both bibliometric and network analysis techniques enabled us to depict a clear and more objective visualization of the emerging intellectual structure in social sciences and management studies related to the Industry 4.0. This methodology can be used by other researchers conducting systematic quantitative literature reviews in their respective fields of study.

Second, **Chapter 3** through developing and quantitatively exploring the concept of online robotic discourse shows how online reviews mentioning service robots can be seen as a useful means to track the diffusion and adoption of this form of innovation over time. This implies that methodologically future researchers could leverage online robotic discourse to inform their investigations related to the introduction of service robots in companies' operations. Third, **Chapter 4**, innovatively conceives a Penalty-Reward contrast analysis deploying text analytics measures stemming from the online robotic discourse, to assess the impact of service robots' evaluation pertaining to the overall customer satisfaction, and service quality is explored at different levels of performance (i.e., positive or negative). Building on extant literature encompassing big data analytics and eWOM (Alaei et al., 2019; Bi et al., 2019), we measured the performance associated to the focal service attribute (i.e., service robot) through the overall sentiment polarity score (i.e., sentiment strength) extracted from the fragments of text related to the analysed aspect. This methodology, can be deployed, on the one hand by companies to track in real-time the impact of the deployment of service robots, and, on the other hand, by future scholars to assess the impact of other specific attributes present in the service offering.

5.4 Practical implications

Noteworthy practical implications stem from the thesis' findings for both companies and policymakers.

At a managerial level, companies aiming to pursue Industry 4.0 initiatives should pay particular attention to the service component of these transformative activities. This is because, as highlighted in **Chapter 2**, services can aid companies to capture the entire value created by the deployment of such projects. To this aim, servitization strategies intertwined with a more customer-centric view could prove effective. Moreover, managers could find useful the overarching framework depicted in **Figure 13**, to understand the themes and economic phenomena that have been linked to the new industrial revolution, with the aim of better informing their internal strategic decisions. In particular, in the service industries domain, as clear from **Chapter 4**, hotel managers aiming to differentiate their service offerings should confidently introduce service robots in their operations. Indeed, the latter are found to improve the perceived overall service quality and customer satisfaction. However, hoteliers should pay particular attention to the online conversations posted on OR platforms since service robots seem to be embedded in highly influential content (see **Chapter 3**), potentially able to have significant repercussions in the customer decision-making process. As such, they can use the novel methodology deployed in **Chapter 4** to track in real-time how the performances of service robots are impacting guests' evaluation of their stay. The techniques developed can also be used with internal consumers' data belonging to the hotel. This would ultimately allow them to monitor the deployment of service robots in companies' operations as well as to timely respond to any significant issue emerging from robot-enabled service encounters. Finally, hotel managers should be aware of the fact that service robots can soon become a commonality in the marketplace. As such, they should constantly try to innovate their service offering pertaining to this new form of innovation.

As far as policymakers and governments are concerned, they could find useful the graphical representation of the 4th Industrial Revolution in **Figure 2**, to understand what the key players and technologies in the Industry 4.0 landscape are, and in turn compare them with their own initiatives and understanding of the phenomenon. Besides, the overarching framework depicted in **Figure 13** could provide useful ground to critically assess their existing policies and better inform their future developmental plans. Referring to the evolution of the new industrial revolution, we could expect policymakers to soon follow the transition suggested by the German government with the Smart Service World plan (German Federal Ministry, 2017), changing their emphasis from manufacturing and production to services and the service industries. Policies and plans in this direction will guide investments for an efficient service innovation that, as suggested by the European Commission (2016a), would eventually allow companies to capture the entire value created by the deployment of Industry 4.0 initiatives. As such, the digital transformation of the global economy will drive our society to experience a new hybrid service economy made of Smart Services which merge products and services in a unique bundle (German Federal Ministry, 2017) and a step closer to the materialization of the 4th Industrial Revolution. However, government should ponder in advance the effect of this disruptive transition of the global economy. Indeed, despite calling for a global adoption of service robots in hotels' operations, the results of **Chapter 4** can potentially exacerbate the debate about societal issues pertaining to the introduction of this form of innovation. For instance, scholars and practitioners have envisioned potential repercussions in the taxation systems and, most notably, employment challenges especially concerning the decency and sustainability of work conditions (Davenport, 2019; Huang and Rust, 2018, Webster and Ivanov, 2020;Tuomi et al., 2020b). Thus, in this climate of uncertainty, policymakers are called to timely act and actively support the transition to a more automated service economy, avoiding being caught unprepared when the global adoption rate will surge dramatically.

5.5 Limitations

This thesis presents some limitations, that are mainly related to the sample selected and to the methodologies deployed in the analysis.

Regarding the sample, both **Chapters 3** and **4** rely on a convenience sample of hotels having pioneered the introduction of service robotics in their operations. As such, the sample was not random, but due to the extensive research performed it should reflect the current landscape of hotels adopting service robots (mainly related to robot butlers). By leveraging on a random and more balanced sample, future researchers could strengthen the generalisability of this thesis's results and perhaps investigate the impact of specific types of service robots. Besides, the online conversations analysed for **Chapters 3** and **4**, are only collected from one OR platform, namely TripAdvisor. Despite being the largest community-based OR platform, to ensure the generalisation of the results, scholars could extend the current research design embedding data from other OR platforms (e.g., Booking.com or Yelp). Another source of bias for the analysis of *online robotic discourse* can be related to the specific moment in time when data was collected. Indeed, as previously mentioned, service robots have only recently been introduced in business operations and this could undermine guests' evaluations of this service attribute. In the long term, consumers could be less prone to accept robotics service failures and this could have a detrimental effect on their perceived levels of satisfaction and distinctiveness of this feature when judging the service experience. Future studies exploiting a longitudinal research design with a longer time frame can reveal how and when this transition happens.

The second set of limitations refer to the methodologies deployed. In fact, despite the several robustness checks performed in **Chapter 4**, endogeneity could still be an issue. This is mainly due to the fact that individual characteristics can influence the consumers' attitude towards service robots (Ivanov et al., 2018a; Wirtz et al., 2018). However, in the secondary data collected, these features are largely missing in the reviewer's profile. Controlling for this set of attributes would help to validate **Chapter's 4** findings. Yet, most notably, the ultimate form of validation would come from conducting field experiments (Viglia and Dolnicar, 2020) collecting primary data related to the human-robot interaction. This would eventually rule out any potential confounding effect. Nonetheless, without leveraging on ORs data we would not have been able to collect and analyse such an abundant volume of information related to human-robot interactions. Methodological limitations stem also from the systematic quantitative literature review conducted in **Chapter 2**, especially related to the bibliometric and network analysis techniques deployed. Indeed, on the one hand, bibliographical coupling (1) favours documents with a long reference list, making for instance literature reviews more likely to be embedded in the analysis; (2) does not capture the underlying mechanism bringing scholars to cite a specific document (Zupic and Čater, 2015). On the other hand, the Louvain algorithm used to create the final network requires researchers to filter important documents beforehand. For this reason, in line with other scholars in the field, we applied network analysis on diverse sets of documents obtained leveraging on different coupling thresholds.

5.6 Research Agenda

Despite future researchers building on the limitations presented in the previous section, a clear research agenda stems from the findings and concepts put forward by this thesis.

First, as far as scholars in management and social sciences aiming to investigate the 4th Industrial Revolution are concerned, they can use the overarching framework provided in **Figure 13** as a reference point for their study. This would help them more precisely position their studies in the most suitable Industry 4.0 stream of literature, clearly identifying the research gaps they aim to uncover. Moreover, they can extend and strengthen the framework using the knowledge gained in their examinations. Second, **Chapter 2** highlights the importance of scholarly effort related to the new industrial revolution to be directed toward service and the service industries. Conceptual and especially empirical investigations are needed to make sense of the potential evolution of the phenomenon in the service domain. Third, and related to the latter point, it would be crucial to understand the antecedents and consequences of the application of Industry 4.0 technologies, and design principles within the tertiary sector to clearly discern how different entities are shaping the transition of the new industrial revolution. As suggested by the findings of **Chapter 2**, a diverse set of theoretical lenses and emerging research approaches can be used as a theoretical ground for future studies, namely institutional theory, digital entrepreneurship, service-dominant logic, and business model innovation. In particular, managerial researchers should pay particular attention to the antecedents and consequences of the infusion of artificial intelligence in robots/machines for services innovation practices, since this promises to disrupt the consumer experience. As such, empirical examinations could begin highlighting the peculiarities of this technological pillar of Industry 4.0.

Fourth, as far as scholars exploring the role of service robots are concerned, the concept of *online robotic discourse* and related analytics could be deployed to: (1) inform research pertaining to the diffusion and adoption of this form of innovation (Rogers, 2003); (2) inform research related to human-robot interactions (Newell and Card, 1985), in the tourism domain (Tussyadiah, 2020). On the one hand, this would generate valuable knowledge for companies on the processes connected to the introduction of service robots in their operations and aid them in tailoring the value offer associated with service robots. On the other hand, an in-depth investigation of *online robotic discourse* would strengthen scholarly knowledge about robot-enabled service encounters. At the intersection of these two research domains, leveraging on the results reported in **Chapter 4**, scholars could also explore whether and how features at the individual, firm, or robot level could act as moderators or mediators in the relationship between service robots and perceived service quality.

In conclusion, following the abovementioned research trajectories would be beneficial to bridge the two nascent innovation research streams looking at the Industry 4.0 in manufacturing (i.e., Hermann et al., 2016; Müller et al., 2018a) and the digital transformation of services (i.e., Rust and Huang, 2014; Huang and Rust, 2018) building a joined-up body of knowledge revolving around the 4th Industrial Revolution.

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Appendices

Appendix 1. *Most cited papers among the retrieved documents (Chapter 2)*

Cited	Authors	Year	Document Title	Type of Document	Journal Title
43	Kagermann, H., Wahlster, W., Helbig, J.,	2013	Recommendations For Implementing The Strategic Initiative Industrie 4.0: Final Report Of The Industrie 4.0 Working Group	Report	
33	Lee, J., Bagheri, B., Kao, H.A.,	2015	A Cyber-Physical Systems Architecture For Industry 4.0-Based Manufacturing Systems	Article	Manufacturing Letters
31	Hermann, M., Pentek, T., Otto, B.,	2016	Design Principles For Industrie 4.0 Scenarios	Conference Paper	49Th Hawaii International Conference On System Sciences (Hicss)
30	Lee, J., Kao, H.-A., Yang, S.,	2014	Service Innovation And Smart Analytics For Industry 4.0 And Big Data Environment	Conference paper	Procedia Cirp
24	Lasi, H., Fettke, P., Kemper, H.G., Feld, T., Hoffmann, M.,	2014	Industry 4.0	Article	Business & Information Systems Engineering
24	Porter, M., Heppelmann, J.,	2014	How Smart, Connected Products Are Transforming Competition	Note	Harvard Business Review
22	Yin, R.K.,	2014	Case Study Research Design And Methods	Book	
21	Kotha, S., Swamidass, P.M.,	2000	Strategy, Advanced Manufacturing Technology And Performance: Empirical Evidence From Us Manufacturing Firms	Article	Journal Of Operations Management
21	Fornell, C., Larcker, D.F.,	1981	Structural Equation Models With Unobservable Variables And Measurement Error: Algebra And Statistics	Article	Journal Of Marketing Research
20	Barney, J.B.,	1991	Firm Resources And Sustained Competitive Advantage	Article	Journal Of Management
18	Stock, T., Seliger, G.,	2016	Opportunities Of Sustainable Manufacturing In Industry 4.0	Conference Paper	Procedia Cirp

16	Brettel, M., Friederichsen, N., Keller, M., Rosenberg, M.,	2014	How Virtualization, Decentralization And Network Building Change The Manufacturing Landscape: An Industry 4.0 Perspective	Article	International Journal of Information and Communication Engineering
15	Wang, S., Wan, J., Li, D., Zhang, C.,	2016	Implementing Smart Factory Of Industrie 4.0: An Outlook () Int. J. Distrib. Sens. Netw.,	Article	International Journal of Distributed Sensor Networks
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13	Atzori, L., Iera, A., Morabito, G.,	2010	The Internet Of Things: A Survey	Article	Computer Networks
13	Kagermann, H.,	2015	Change Through Digitization-Value Creation In The Age Of Industry 4.0	Book	

__Appendix 2.__ Authorship Form Paper 1 (thesis's Chapter 2)

1 June 2019, Reading

Authorship contribution

To the **Chapter 2**

We defined each author's contribution to the paper as follows:

Conception or design of the work – Matteo Borghi and Prof. Mariani (10 and 10 points out of 100 each)

Literature review – Matteo Borghi solely (5 points out of 100)

Data Collection – Matteo Borghi solely (5 points out of 100)

Data analysis and interpretation – Matteo Borghi and Prof. Mariani (10 and 10 points out of 100 each)

Drafting the article – Matteo Borghi solely (10 points out of 100)

Critical revision of the article – Matteo Borghi and Prof. Mariani (20 and 20 points out of 100 each)

As such, we define contributions to the chapter in total as follows: Matteo Borghi 60% and Professor Marcello M. Mariani 40%.

Signatures:

[redacted]

Appendix 3. *Authorship Form Paper 2 (thesis's Chapter 3)*

1 March 2020, Reading

Authorship contribution

To the **Chapter 3**

We defined each author's contribution to the paper as follows:

Conception or design of the work – Matteo Borghi and Prof. Mariani (10 and 10 points out of 100 each)

Literature review – Matteo Borghi and Prof. Mariani (5 and 5 points out of 100 each)

Data Collection – Matteo Borghi solely (10 points out of 100)

Data analysis and interpretation – Matteo Borghi solely (10 points out of 100)

Drafting the article – Matteo Borghi solely (10 points out of 100)

Critical revision of the article – Matteo Borghi and Prof. Mariani (20 and 20 points out of 100 each)

As such, we define contributions to the Chapter in total as follows: Matteo Borghi 65% and Professor Marcello M. Mariani 35%.

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Appendix 4. *Authorship Form Paper 3 (thesis's Chapter 4)*

29 October 2020, Reading

Authorship contribution

To the **Chapter 4**

We defined each author's contribution to the paper as follows:
Conception or design of the work – Matteo Borghi and Prof. Mariani (12 and 12 points out of 100 each)
Literature review – Matteo Borghi and Prof. Mariani (6 and 6 points out of 100 each)
Data Collection – Matteo Borghi solely (12 points out of 100)
Data analysis and interpretation – Matteo Borghi solely (12 points out of 100)
Drafting the article – Matteo Borghi solely (16 points out of 100)
Critical revision of the article – Matteo Borghi and Prof. Mariani (12 and 12 points out of 100 each)

As such, we define contributions to the chapter in total as follows: Matteo Borghi 70% and Professor Marcello M. Mariani 30%.

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