Innovation analytics and digital innovation experimentation: the rise of research-driven online review platforms

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Abstract

Big data analytics constitute one of the driving forces of the fourth industrial revolution and represent one of the founding pillars of Industry 4.0. They are increasingly leveraged to create business insights from online reviews of products and services by a wide range of organizations and firms. In this work, we develop a typology of online review platforms (ORPs) and describe a novel platform, *research-driven online review platform* (RORP), that combines the science and rigor of very large-scale, low-cost, fast-paced, and complex digital experimentation using real-world customers on digital platforms with the power of modern AI-based big data analytics capabilities (BDAC) to generate novel innovation insights for the digital age. Using multiple real-world case studies, we illustrate how RORPs operate and deliver value through innovation analytics, and serve as a powerful tool for digital innovation experimentation, enabling firms to innovate more effectively and transform their business models to adapt to rapidly changing market conditions. We shed light on the BDAC requirements, as well as the benefits and challenges of using RORPs and innovation analytics, particularly in the post-COVID-19 world, and offer strategic and operational implications for entrepreneurs and innovation managers.

Keywords: big data analytics, online review platforms, digital innovation experimentation, innovation analytics, entrepreneurship.

1. Introduction: Nobody knows anything?

Almost 40 years ago, Hollywood legend William Goldman wrote, "Nobody knows anything...... Not one person in the entire motion picture field knows for a certainty what's going to work. Every time out it's a guess and, if you're lucky, an educated one" (Goldman, 1983, p. 39). Since then, the "Nobody knows anything" circumlocution has become a mantra in the movie industry, suggesting that success is the by-product of guesses, gut feelings, and intuition. Today more than ever, innovation managers and entrepreneurs often operate under great levels of market uncertainty, particularly when the new products and services they develop have to cater to rapidly changing customer needs, desires, and preferences. For example, in industries such as apparel, music, travel, and consumer electronics fads and trends that make or break new products can be very dynamic, making reactive innovation strategies quite ineffective. Traditional market research tools such as focus groups and online customer surveys have limited application in such contexts. Even the application of sophisticated data analytics tools on social media feeds offers limited insights, especially when the products being developed are unique, one-off (e.g., music album, movie) and aimed at niche and emergent markets. At the same time, consumer goods companies in a wide range of industries have increasingly relied on online reviews (ORs), i.e., real-time customers' appraisals of goods and services (Hennig-Thurau et al., 2004), to generate marketing analytics useful for operational decisions such as pricing, improving customers' purchasing decisions and service, increasing product visibility and brand image, enhancing sales, and reducing inventory costs. The value of such OR-based marketing analytics has been discussed widely and is well established (e.g., Wedel and Kannan, 2016). However, in the past few years, the field of ORs and related analytics has taken on a new trajectory (Davenport, 2017), one that marks a shift from a traditional marketing focus to an innovation focus, i.e., a move from marketing analytics to innovation analytics (Kakatkar et al., 2020). This latter type of analytics involves the generation and use of data-driven insights and visualizations within innovation processes and seeks to endow entrepreneurs and innovation managers with newfound data analytics capabilities to manage uncertainties in product and service innovation. We propose that innovation analytics, and specifically OR-based digital innovation experimentation, forms the frontier in innovation management in the digital age.

In this study, we focus on a novel and important platform-based tool to generate OR-based innovation analytics—what we call *research-driven online review platforms* (RORPs)—that finds particular application in online consumer markets and holds the potential to create strategic and transformative value for companies across industries. RORPs combine the science and rigor of experimentation (involving large numbers of pre-selected testers or potential customers from across the world) on online review platforms (ORPs) with the power and capabilities of modern data analytics and AI-based tools to generate novel innovation insights. It is important to study RORPs as they are increasingly deployed by managers and entrepreneurs willing to innovate in the digital age. Understanding RORPs is also critical to extending the nascent yet promising research stream on innovation analytics (Kakatkar et al., 2020).

While the notion of innovation experimentation is not new (Thomke, 2003), even in online settings (Bojinov et al., 2020; Kohavi and Thomke, 2017), *experimentally crowdsourced and solicited ORs* by RORPs allow for very large-scale, low-cost, fast-paced, and complex experimentation using real-world customers on digital platforms and the mining of big data from such experiments using sophisticated ML and AI-based analytic techniques, thereby radically transforming the very domain of *digital innovation experimentation*.

Our purpose in this article is to: (1) develop a typology of ORPs; (2) define RORPs and describe how they operate and deliver value; (3) explain how innovation managers and entrepreneurs can carry out digital innovation experimentation and use such RORPs to innovate more effectively and transform their business models to adapt to rapidly changing market conditions; and (4) introduce and substantiate digital experimentation analytics capabilities as a type of big data analytics capabilities (BDACs). To achieve the aforesaid purpose, over the last three years we conducted extensive research that included comparative analysis of over 70 ORPs globally which informed our conceptualization of RORPs. Following this, we also carried out detailed case studies of two firms that serve as RORPs—US-based First Insight and UK-based SoundOut. We interviewed multiple managers in the two companies. Furthermore, we interviewed innovation managers and senior executives in companies that use RORPs, such as Universal, Sony, Warner, CBS, New Look, Tesco, and Zalando. We use these case studies and interviews with managers, as well as other sources of data, to illustrate the key ideas proposed in this paper and to address a focal research question: How are innovation analytics and digital innovation experimentation being developed and leveraged to innovate in the digital age?

Accordingly, not only do we contribute to the literature and knowledge at the intersection of data analytics, ORPs, and innovation, but we observe the advent of an ecosystem of digital businesses (Zahra and Nambisan, 2011) that has the potential to empower digital innovation experimentation that in the digital age and in the post-COVID-19 world has become "both a necessity and an expectation" (McKinsey, 2020) as the pandemic is changing how companies assess and evaluate which new products to take to market in a remote work environment. Further, as Greg Petro, CEO of First Insight noted, "The rate of change in the marketplace is increasing dramatically in the post COVID-19 environment and companies that do not engage with their target customers about current priorities, changes in purchase behaviors, and valuations of upcoming new products, services or solutions are likely to be doomed."

To address our research question, the study is structured as follows. In the second section, we review literature on (i) data analytics as a disruptive technology underpinning the fourth industrial revolution; and (ii) ORPs as a source of data analytics and online experimentation. The third section describes the data and methods deployed. The fourth section describes the findings. Section five elucidates the theoretical contributions and the practical implications. We conclude by identifying some of the study limitations and presenting a succinct yet meaningful research agenda.

2. Literature review

2.1 Big data and data analytics

Human and business activities are increasingly permeated by digital technologies that are profoundly modifying the way enterprises do business. This modification has been termed a digital evolution by some scholars and a digital revolution by some others (Kim, 2018; Reischauer, 2018), generally recognizing that we are witnessing the emergence and consolidation of a fourth industrial revolution heavily supported by national governments and supranational institutions.

This fourth industrial revolution, originally named Industrie 4.0 (Kagermann et al., 2013), and later renamed Industry 4.0 (Rüßmann et al., 2015), is driven by nine underpinning technologies, entailing: horizontal and vertical integration systems, autonomous robots, simulation, cybersecurity, industrial IoTs, cloud, additive manufacturing, augmented reality, and big data and analytics. This latter technology—big data and analytics—is proving critical for value creation across multiple value chains, verticals, and industries, and indeed is becoming the new oil of the digital economy (The Economist, 2017). For this reason, big data and analytics have become increasingly central in the business and management literature (Davenport et al., 2012; George et al., 2014; Mariani, 2019; Mariani and Borghi, 2021a, 2021b;

McAfee et al., 2012; Wamba et al., 2015) beyond computer science (Chen et al., 2014; Jagadish et al., 2014; Madden, 2012; Sagiroglu and Sinanc, 2013).

Departing from early definitions of big data that have identified a set of features characterizing uniquely their notion under the “3Vs” acronym, standing for Volume/Velocity/Variety of data (Laney, 2001), more recently scholars have focused on big data analytics (BDA) (Batistič and van der Laken, 2019), defined as a process allowing the uncovering of hidden patterns in apparently unrelated data points, and bringing actionable managerial insights (Mariani and Fosso Wamba, 2020; Wamba et al., 2020).

BDA has been identified as critical to enriching business intelligence with a view to competitors (e.g., improvement of competitive strategies), customers (e.g., maximization of customer satisfaction), suppliers (e.g., efficient management of supply chain risks), and a number of stakeholders along the value chain and systems (Davenport, 2017; Mariani et al., 2018; Williams, 2016). Improved business intelligence through BDA has been found to enhance firms’ performance and organizational agility in a number of industries (Dubey et al., 2019) as well as support companies’ Industry 4.0 strategies (Santos et al., 2017).

As big data contains information about products, services and a number of stakeholders whose understanding is critical to creating value in the Industry 4.0 context (Kagermann, 2015), BDA enables improved organizational performance and competitive strategies, making companies more competitive in the aforementioned context. However, several scholars have argued that BDA alone is not enough to make a difference, as companies need to possess BDACs to pursue higher levels of performance (Mikalef et al., 2020).

Extant literature has defined BDACs in relation to the resources that are necessary to build a big data analytics capability, to be defined as a firm’s ability to gather, combine, and use its big data-specific resources (Gupta and George, 2016). More specifically, by leveraging the resource-based theory of the firm, Gupta and George (2016) identify three major types of resources underpinning BDACs: tangible resources (including data, technology, and basic resources such as time and investment); human resources (entailing managerial skills such as analytics acumen and technical skills such as education and training pertaining to data-specific skills); and intangible resources (encompassing data-driven culture and intensity of organizational learning).

Leveraging the definition put forward by previous literature (e.g., Gupta and George, 2016), Mikalef et al. (2020: p.2) describe BDACs as “the ability of a firm to effectively deploy technology and talent to capture, store, and analyze data, toward the generation of insight”. BDACs have been recently found to be conducive to a more streamlined value chain (e.g., Srinivasan and Swink, 2018) and better performance (Elia et al., 2021; Mikalef et al., 2019).

A number of organizations are deploying big data sourced from user-generated content (e.g., ORs and social media posts) to generate meaningful BDA through their own or third-party BDACs. In Section 2.2 we review the literature that has deployed analytics from ORs to improve business intelligence in today’s digital markets.

2.2 Online review platforms, online review analytics and online experimentation

The advent, development, and consolidation of online review platforms has engendered a proliferation of online reviews (ORs) in a wide range of industries. ORs have been found to be the second most popular source of information after family and friends’ word of mouth before any purchase (Nielsen, 2015). Accordingly, they have been examined by scholars in a multitude of disciplines. Over the last 15 years, computer and data scientists have examined various features and characteristics of ORs—including ratings, volume, identity disclosure, readability, and informativeness—and the use of different data analysis techniques, including data mining, machine learning, sentiment analysis on OR big data (Boyd and Crawford, 2012), and more traditional statistical methods (Chong et al, 2016; Mudambi and Schuff, 2010).

Partially leveraging insights from the economic mechanisms underlying multi-sided platforms (Evans and Schmalensee, 2016), marketing scholars have examined the processes through which consumers produce/adopt ORs (Hennig-Thurau et al., 2004) as well as the influence of ORs and related analytics on consumer decision-making under the guise of customer satisfaction, trust, attitude, buying intention, and experience (e.g., Forman et al., 2008; Filieri and Mariani, 2021; Mariani et al., 2018; Mariani and Matarazzo, 2021), and on business performance in the form of sales, revenues, efficiency and profits (e.g., Chevalier and Mayzlin, 2006; Chintagunta et al., 2010; Chong et al., 2016; Hu et al., 2014; Mariani and Borghi, 2020; Mariani and Visani, 2020). Extant marketing literature indicates that the effect of OR analytics (in the guise of valence, volume, variance, sentiment, etc.) on sales depends also on factors related to the context (You et al., 2015). To summarize, marketing scholars so far have mainly focused on OR marketing analytics that can generate value for two categories of individuals: (a) online customers seeking information about products; and (b) marketers and platform managers trying to maximize product revenues.

Over the last couple of years, the scholarly attention of researchers dealing with analytics leveraging ORs has shifted from marketing to innovation analytics. Innovation analytics involves the generation and use of data-driven insights and visualizations within innovation processes and seeks to endow entrepreneurs and innovation managers with newfound capabilities to manage uncertainties in product and service innovation (Kakatkar et al., 2020). For instance, Kakatkar et al. (2020) offer a few case studies of how large volumes of user-generated content (in the form of online posts and online forums) allowed firms to identify consumer needs or influencers. Accordingly, there is a close relationship between ORPs, OR analytics and the use that can be made of AI technology to generate analytics. More specifically, ORPs host the largest volume of user-generated content pertaining to consumers' opinions and evaluations of products and services (Babić Rosario et al., 2016). Online reviews from ORPs have been largely used by computer and data scientists and practitioners, as well as information management scholars, to better understand consumers' perceptions and behaviors, and OR generation and consumption (e.g., Hong et al., 2017; Zhou et al., 2018). As explained by Kakatkar et al. (2020), AI can substantially influence four main drivers of analytics from user-generated content in general (ORs being a part of that content): (1) specification of objectives; (2) data collection and preparation; (3) modeling; and (4) value capture. For instance, they report that AI was deployed by a German manufacturer of personal care products to carry out an analysis of a vast amount of user-generated content on consumer needs with a twofold aim: to separate plausible consumer needs and the problems they implied from mere online chatter and promotional content; and to engender descriptive clustering of the identified needs.

In this article we focus on a specific form of user-generated content, namely experimentally crowdsourced ORs, as they can generate a superior raw material for digital innovation experiments and ultimately innovation analytics and, once enabled by AI technology, they can suitably become the frontier in data-driven innovation management and digital entrepreneurship.

The notion of innovation experimentation is not new (Thomke, 2003), even in online settings (Bojinov et al., 2020; Kohavi and Thomke, 2017). Extant research has shown that online experiments can be a game changer for digital technology giants such as Facebook, Amazon, Microsoft, and Google, when it comes to marketing and innovation decisions related to their platforms (Thomke, 2020). However, it is less clear to what extent companies that are not digital natives are embracing digital experimentation. Moreover, we do not know much about how innovation analytics capabilities for digital experimentation have been shaped and evolved over time. Accordingly, in this paper, after tracing the evolution of ORPs and building a typology of ORPs, we will illustrate how data analytics capabilities for digital experimentation vary across ORPs.

3. Methodology

This study adopts a qualitative research design and employs longitudinal case study technique (Eisenhardt, 1989; Pettigrew, 1990; Yin, 2009). There are two reasons for this. First, both innovation analytics and digital innovation experimentation involving ORPs are nascent and complex phenomena whose nature has not been properly studied in the extant literature. Indeed, so far, most studies on innovation analytics and digital experimentation have had only a practice orientation (e.g., Kakatkar et al., 2020; Thomke, 2020). A qualitative approach allows a fine-grained and nuanced appreciation of how innovation analytics and digital innovation experimentation work and how they can benefit innovation managers and entrepreneurs. Second, we draw on the notion of qualitative pluralism (Cornelissen, 2017), which implies how diverse qualitative research techniques could be useful to enhance both theoretical and empirical research development, particularly when little evidence is accessible.

We illustrate the research approach adopted as follows. In terms of *empirical setting*, we have focused on ORPs in general, and more specifically on those ORPs that are capable of generating innovation analytics. To develop a typology of ORPs, we collected data on more than 70 online platforms currently hosting the highest share of ORs of products, services, businesses, and brands, including: a) independent online review websites such as Yelp and Trustpilot; b) e-commerce websites such as Amazon, Alibaba, eBay, and Expedia; c) online phone directories such as Yell; d) search engines such as Google and Yahoo; e) social networking and microblogging sites such as Facebook and Twitter; f) sharing economy platforms such as Airbnb, Uber, and Lyft; and g) intermediation apps such as Just Eat and Deliveroo. To conceptualize research driven online review platforms (RORPs) and explain how they create value by means of innovation analytics and digital innovation experimentation, we selected two real-world leading platforms/organizations which represent revelatory cases (Yin, 2009) able to shed light on the new phenomenon investigated: the US-based firm First Insight and the UK-based firm SoundOut. The two firms are leaders in innovation analytics and digital innovation experimentation as their solutions and services have been adopted internationally by an increasing number of firms across different industries and verticals over the past 15 years. We leveraged multiple data sources: 1) public information about the ORPs and those firms using ORPs for product innovation; 2) data stemming from interviews with the selected ORP managers and senior level managers involved in product innovation in firms active in media and entertainment, fashion and retail; and, 3) annual reports as well as internal documents such as strategic and operational plans, memos, and presentations of the focal organizations. The unit of analysis was ORPs with the level of analysis being the innovation project that the ORPs supported. Finally, in relation to data analysis, the aforementioned three types of data were triangulated and were the object of validity and reliability assessment (Creswell and Creswell, 2017) which involved three independent researchers.

3.1 Data collection

Primary and secondary data were collected at different moments in time both before and during the COVID-19 pandemic and roughly in three partially overlapping phases. In the first phase (from March 2017 to December 2018) we collected secondary data about ORPs and conducted in-depth open-ended interviews with a number of senior and middle managers selected through random sampling (Pratt, 2009), and employed by organizations entailing independent online review websites, e-commerce websites, online phone directories, search engines, social networking and microblogging sites, sharing economy platforms and, intermediation apps. During the interviews with managers of ORPs, we collected contact information about their major business clients; this list was employed to identify and contact senior-level product innovation managers of ORP business clients, who were later interviewed. The interview data and secondary data collected in the first phase were used to explore the evolution of ORPs and gain an understanding of their similarities and differences. This comparative analysis helped us to move on and focus on the conceptualization of RORPs in phase two.

In the second phase (from April 2018 to December 2019), interviews were conducted with a number of managers of two leading ORPs whose core business entails the generation of innovation analytics as well as digital innovation experimentation: the US-based First Insight and the UK-based SoundOut. Moreover, we conducted in-depth semi-structured interviews with senior managers of firms that deploy innovation analytics to make product innovation decisions across different industries such as big media and entertainment, fashion, and retail. Some of these companies include Universal, Sony, Warner, CBS, New Look, Tesco, and Zalando. This phase was critical for the conceptualization of RORPs and to understand the extent to which digital experimentation and analytics capabilities were present across the different types of ORPs.

In the third phase (from March to October 2020), we decided to conduct additional interviews to capture emerging challenges and opportunities for RORPs brought about by the COVID-19 pandemic. This was useful to better contextualize the increasing importance of RORPs in a world where physical testing of new products has become difficult, if not impossible. These further interviews offered additional insights from a larger set of key informants on the way RORPs were adapting to the pandemic and helped us validate the findings stemming from the interviews conducted in the second phase.

Overall, 43 interviews were conducted with 26 key informants. The topics covered through the in-depth open and semi-structured interviews with ORPs' managers entailed: how the platform operates; how they collect, process, and analyze data from ORs to generate analytics; the type of value that they generate; the platform's stakeholders for which value is generated; the purposes for which OR data are generated; the resources (intangible, tangible and human) they use; and how their business models have evolved over time (also in light of COVID-19). The topics covered in interviews conducted with senior-level managers involved in supporting product innovation by means of analytics include: the features of their ongoing innovation projects; the extent to which they use analytics and BDA to make product innovation decisions; and the extent to which they carry out or outsource digital experiments before making product innovation decisions (e.g., new product testing). The duration of interviews ranged from 49 to 127 minutes and notes were taken by a research assistant and one of the researchers. Real-life stories pertaining to the development and use of innovation analytics and digital innovation experimentation were reported by the respondents. Interview data were triangulated with public information about ORPs and those firms using ORPs for product innovation and archival sources such as annual reports and other documents entailing strategic and operational plans, memos and presentations of the organizations studied. The use of multiple sources allowed us to gain a deeper appreciation of the phenomenon examined.

3.2 Data analysis

We deployed template analysis in keeping with a tradition of qualitative research (e.g., Crabtree and Miller, 1999; King, 2004) developed to understand more carefully management and information management issues. Consistent with the key guidelines of template analysis (e.g., King, 1998; King, 2004), a research assistant and one of the researchers independently read 18% of the printed interview transcripts and carried out a manual coding. The coding implied either devising a new theme, associating an a priori theme, or modifying an existing one. The procedure enabled us to produce a preliminary template entailing a number of themes. Then, the themes discovered were grouped and clustered into a smaller number of higher-order codes with the aim of describing broader themes. Afterwards the remaining 82% of the printed interview transcripts were independently read and manually coded by a research assistant and one of the researchers. Overall and after the revision of the existing themes, this generated a final template. Furthermore, a second researcher (not involved in the coding) performed a quality check during the development of both the preliminary (first) template and the final template, to make sure that preconceptions and assumptions of the research assistant and the other researcher had not systematically biased the analysis. Eventually the final template was used to engender the results.

4. Findings

4.1 The evolution of ORPs and the emergence of RORPs

Since at least the beginning of the twentieth century (and long before the advent of the Internet), customer reviews have played a major role in shaping business success in large consumer-oriented economies such as those of the United States and Europe. Trust in companies and businesses was an irreplaceable condition to convince consumers to purchase products and services. The US-based Better Business Bureau (BBB)—founded in 1912—was the first non-profit organization to engage in consumer protection and marketplace trust. It put in place a mechanism of ratings for businesses and accredited businesses adhering to the BBB Code of Business Practices. The American magazine *Consumer Reports* was established a couple of decades later (in 1936) by the Consumers Union, a non-profit organization interested in public education, consumer-oriented research, unbiased product testing, and advocacy. It published (and still publishes) reviews and comparisons of products and services based on reporting and results from its in-house testing laboratory and survey research center. Similarly, Consumers' Association, the largest consumers' organization in the UK, has since the 1950s engaged in consumer protection and marketplace trust by independently testing and rating new products and services and by publishing the monthly magazine *Which?*. While these pioneers of offline product reviewing have survived and even shifted to publishing their magazines online, with the advent of the Internet, other digital platforms emerged that allowed customers to directly take on the role of reviewing and rating products, services, and businesses.

Indeed, online reviews are perhaps the most widespread form of real-time customer's feedback currently available to firms, managers, and entrepreneurs in the digital economy. They are generated online by both business customers and end consumers and are hosted by a number of different ORPs, including independent online review platforms (e.g., Trustpilot, TripAdvisor), e-commerce platforms (e.g., Amazon, Alibaba, Expedia), search engines (e.g., Google, Yahoo), social media platforms (e.g., Facebook), and sharing economy platforms (e.g., Airbnb, Blablacar, Lyft).

Based on an in-depth analysis of the similarities and differences of more than 70 ORPs, we classify them into three types: (a) information-driven ORPs; (b) transaction-driven ORPs; and (c) research-driven ORPs. While the first two types have been in existence for a long time, the third type is more emergent and novel. And, the emergence of the RORPs implies a shift in focus from supporting marketing and operations to facilitating innovation and business transformation. We briefly describe each type.

Information-driven ORPs (IORPs) host mainly ORs of existing products and services that are not transacted on the platform itself, but elsewhere online. They include (independent) ORPs such as Yelp and Trustpilot, social networking sites such as Facebook, online phone directories such as Yell, and search engines such as Google. ORs are crowdsourced and written by individuals who register on the website (reviewers can be either end consumers or business customers) and typically the reviewers and their reviews are not verified by the platform manager. Importantly, reviewers are not rewarded by the platform manager for their reviews.

Some IORPs implement algorithms to check the authenticity of ORs and mechanisms to differentiate between helpful and unhelpful reviews. The reviews on IORPs are visible to all Internet users and the main purpose of IORPs is to deliver ***informational value*** to other users by providing easy and fast access to information about peer customers' perceptions and experiences with businesses and their products and services. While platform managers can use data from IORPs to profile and segment their users and to even facilitate location-based marketing (for example, by businesses selling advertisements on Facebook), such value is often secondary.

Transaction-driven ORPs (TORPs) host ORs of existing products and services that are transacted on the platform itself. They include e-commerce websites such as Amazon and Booking, and sharing economy platforms such as Airbnb and Uber. The reviews on TORPs are written by individuals who are actual customers and relate to real and certified transactions. Platform managers often provide incentives or rewards to reviewers (and such rewards may be linked to the quality and/or quantity of reviews submitted). In addition, TORPs often have mechanisms (e.g., customer votes, algorithms) to assess the quality and authenticity of the reviews as well as to filter the reviews based on different criteria (e.g., customer rating, helpfulness). TORPs are part of the core business of the platform and designed to deliver ***transactional value***—for example, to help improve customers' purchasing decision process (and journey) and operational benefits such as increased product visibility and brand image, improved customer service, enhanced sales, and reduced inventory costs. Data from TORPs have been used by platform managers to analyze, in real time, customer satisfaction with a good/service, track the online customer journey and behavior, profile and segment their users, make pricing decisions, and optimize product distribution plans. More broadly, analysis of data from TORPs can contribute to enhancing the quality and timeliness of a wide range of operational decisions.

A confluence of factors—including advances in digital technologies, cloud computing, AI, and data analytics, as well as the rapid globalization of markets and the consequent ability to reach potential customers across the world—have enabled the emergence of the next generation of ORPs that cater to discovery and experimentation and support research and innovation in a number of industries. We call these platforms Research-driven Online Review Platforms (RORPs). Increasing numbers of companies across industries have started deploying such RORPs to speed up the testing of their new products and services, predict demand patterns, trigger lean innovation practices, and more broadly, to generate novel market-based insights useful for decision-making in innovation.

The differences and similarities across the three types of ORPs and the typology of ORPs proposed is illustrated in **Table 1**.

[Insert Table 1 about here]

As **Figure 1** indicates, the three types of ORPs signify progressively higher levels of value addition to businesses—from supporting customer purchase decisions to enhancing customer service quality and marketing/operational efficiency to addressing different types of knowledge gaps and uncertainty and enhancing risk management in innovation and entrepreneurship.

[Insert Figure 1 about here]

Given these differences, business managers should carefully select the appropriate ORP based on the type of business value they seek. If the aim is to address the information needs of online customers without any need for supporting a specific business function, then IORPs offer an inexpensive and appropriate approach. For example, this would help enhance product visibility (via online customer reviews) without incurring additional marketing costs. On the other hand, if the aim is to address the transactional needs of online customers (e.g., customer service) and to support the marketing activity of businesses, then TORPs are appropriate. TORPs allow managers to improve existing online customers' experiences and journeys, support purchasing decisions, increase product visibility and product sales, improve customer service, compress inventory costs, support location-based marketing, carry out micro-segmentation of extant customers, and optimize the distribution.

Finally, if the goal is to address the needs of product developers and corporate entrepreneurs, or more specifically, if the intention is to reduce different types of market-related uncertainties and to address specific types of knowledge gaps in innovation or entrepreneurial initiatives, then RORPs form the most suitable solution. More broadly, RORPs allow innovation managers and entrepreneurs to conduct low-cost but very large-scale experiments in digital market labs in ways that would enhance their ability to manage different types of market risks, and thereby, the quality of their innovation decisions. In Section 4.2, we describe RORPs in more detail.

4.2 Research-driven online review platforms

4.2.1 Brief history of sample RORP companies

A brief historical overview of Pittsburgh-based First Insight and UK-based SoundOut is presented in the boxes (Box 1 and Box 2) below.

Box 1: About First Insight

First Insight was founded in 2007 in Pittsburgh, PA (USA) by Mr. Greg Petro, a businessman whose career started in retail with Macy's and Sak's, Inc. and then transitioned to the software and SaaS industry. From this breadth of experience, Greg realized there was a better way for retailers and other businesses to make decisions, and devoted himself to revolutionizing the retail industry. He observed huge limitations and inefficiencies on how retailers selected new items and priced them. Instead of asking target consumers, decisions were made by a select few who relied on their experience and intuition. His passion for removing the gap between companies and consumers, and helping anticipate a product's success before an investment is made, led Greg to found First Insight. His vision was to combine voice of the customer inputs regarding new products and concepts with predictive analytics to help retailers and brands increase product success rate, and associated financial results. He leveraged the internet, mobile device adoption and digital design tools to streamline the time and effort to test new concepts and designs. First Insight revolutionized the industry, and has grown, with over 100 customers around the globe, and offices in London (U.K.) and Chennai (India). Customers include some of the world's leading vertically integrated brands (Gap, Inc., Under Armour), sporting goods companies (Dick's Sporting Goods), department stores (Kohl's, M&S), consumer products companies (Zippo, Crate & Barrel, Hunter Fan, Constellation Brand's Robert Mondavi Wine), and wholesalers (Li & Fung, Caleres). Moving forward, First Insight is expanding into other industries such as travel, leisure, and entertainment, automotive and financial services, providing a next-generation experience management platform that enables companies to create the experience their target consumers want.

Box 2: About SoundOut

SoundOut was started up in 2007 in Reading (UK) by Mr. David Courtier Dutton, a former city lawyer, corporate finance banker and veteran of the dot-com boom. The SoundOut platform was developed in parallel with another of David's startup, Slicethepie, the first crowdfunding website for unsigned artists. Slicethepie's aim was to be the financing engine for the 'new' music industry. The platform was successful in building a loyal community of music fans and SoundOut started offering independent record labels and artists the opportunity to submit songs to the Slicethepie's community and to get market research reports based on the reviews. Later on, the firms embarked on a number of business model iterations and pivots that allowed it to evolve: (a) on to becoming the first reference product tester for soundtrack for independent artists, record labels, and music publishers (2009); (b) then on to becoming the leading provider of data analytics for the major labels (2011); (c) and, subsequently to offering its services to companies in the entertainment vertical by leveraging Application Programming Interfaces (APIs) and to the fashion industry by using predictive analytics (2014). Eventually SoundOut was able to apply at-scale machine learning techniques and AI to position itself as a Software as a Service (SaaS) white label in a number of different industry verticals. Its clients include the major labels (e.g., Universal, Sony, Warner), media and broadcasters (e.g., Vodafone, CBS, TI Media), fashion (e.g., American Apparel, New Look, Timberland) and retail (e.g., Tesco, Zalando, Amazon, Best Buy, Unilever). Overall, after 12 rounds of fundraising (worth £7m) and 5 (financial) near-death experiences, the company currently works with 72 shareholders, has a lean organizational structure (employing 14 people), and is valued at £10 million.

RORPs such as UK-based SoundOut, Pittsburgh-based First Insight and Cincinnati-based 8451 generate ORs and similar digital consumer content[1] experimentally before a product/service is released and with no actual product-related transaction taking place. RORPs deliver strategic and transformational value by generating critical insights (using both predictive and prescriptive analytics) that help bridge knowledge gaps related to the online market potential of a new product or service and quantifying potential customers' (testers') satisfaction before release. As emphasized by the CEO and Founder of SoundOut, their platform "forecast demand when clients have no data about customers", which resonates with the way First Insight leverages the voice of the customer (in the guise of solicited content from social media and consumer panels) to generate actionable consumer-driven predictive results that significantly increase the likely success and forecast accuracy of new products and services.

4.2.2 How RORPs deliver value

Business customers can leverage RORPs to enhance their strategic decisions in areas such as product design optimization, forecasting demand for new products, process innovation, and customer micro-segmentation. As First Insight's Petro notes, "Our customers have used digital innovation experimentation for so many different decision types—from what new products to offer, to how to price them, market them and sell them." Importantly, the insights generated by RORPs have also been used by the commissioning companies to make radical changes to their business models, thereby triggering more transformative changes. RORPs' distinctive features

[1] Online reviews and responses to surveys included in games are one of the items of "customer voice" used by companies such as First Insight.

include *experimentation and discovery*—mining big data from digital market experiments to discover new patterns of customer choices and to guide new product development.

For instance, a number of manufacturers and retailers of apparel, footwear, and home goods such as Marks & Spencer, Kohl's, Hunter Fan, and Crate and Barrel increasingly rely on the predictive analytics generated by First Insight, the world's leading customer-centric RORP, to test new concepts, products, pricing promotions, advertisements and the like. Manufacturers and retailers first identify what innovation decision they are trying to make about the future alternatives. Then, they simply enter names, descriptions, images (sketches, 2D or 3D CAD, photos, or video), and test prices (if available) for the options into the platform. Next, they invite consumers to provide feedback on the innovation alternatives via a structured "game" on their computers, tablets, or mobile phones. By applying AI, ML and Bayesian modeling to online reviews, First Insight is able to generate accurate predictive analytics and insights to enable users to select the options that will most likely be successful, identify the right retail price before release, detect which segments to target, and gauge forecasts for the new items. Similarly, major recording companies (e.g., Universal, Sony, Warner) and radio stations (e.g., CBS radio) use RORPs' analytics to test new tracks before producing them or to select tracks to add to radio playlists. By administering "new to the market" sound tracks to a panel of almost 3 million consumers in both the UK and the US, SoundOut is able to gather their evaluations (in the guise of online reviews) and generate predictive analytics conducive to greenlighting (or not) the production and distribution of a song, hence engendering cost savings for its clients. Manufacturers like Hush Puppies and retailers like Zalando use RORPs to test competing new designs and attributes to understand which of them resonates with the prospective customers, what the right initial price should be, how much inventory to buy, and which customer segment/s to target. Advertisers use RORPs to test new TV and online commercials to understand which are most compelling for different target demographics and also to identify which actors/scenes are most effective across different audiences. FMCG companies such as Unilever use RORPs to check how their brands are perceived and whether new packaging/adverts are reinforcing brand values.

The benefits from RORPs are illustrated by the following six brief case studies of First Insight's and SoundOut's clients. The first case study is that of a leading American specialty retailer of women's casual apparel and accessories, which wanted to know what new boots to offer and if a new trending kitten heel boot would succeed in the market. The vertically integrated retailer tested the kitten heel with First Insight's platform and the consumers' feedback from the test was not encouraging for the item as tested. Therefore, the retailer used the materials to produce a better-scoring style with a comfortable block heel. As a result, the retailer saved $10 million by avoiding kitten heel production, while the new style with a comfortable block heel succeeded. The retailer learned that their cost-conscious customer wants more versatile styles they can dress up or dress down for multiple occasions.

Now consider a second case study of product designers at a global home goods brand who wanted to understand which design themes they should target for their next development initiative for kitchen storage containers. The designers used First Insight to test 11 design themes (e.g., clear, herbs, nature, licensed characters, etc.). The home goods brand selected the top three designs from the test and targeted them based on the age and gender groups that they resonated most with, resulting in a sales increase of +13% to the previous year.

The third case study relates to a global brand producing and selling iconic western boots worldwide. Their original problem was to speed up the development process while cutting costs and time to develop materials and samples. They realized moving the production from Mexico to China would reduce costs and improve manufacturing technology. However, a question emerged: "Would moving the production to China during the initial days of the COVID pandemic impact customer perceptions, especially given the ongoing public health crisis?"

They decided to research these options using First Insight and ran two tests simultaneously to test the country of import (Mexico vs. China) on the same boot assortment. This digital experiment yielded interesting results regarding perceived value: consumers were willing to spend $20 less for boots made in China compared to boots made in Mexico. Further, consumers' comments analysis also indicated a negative connotation with moving manufacturing to China. This led the company to avoid relocating its production to China since the total financial impact was not as expected.

The fourth case study is that of a major record label. The client's music artist (an internationally popular band) was going to release a new album, but the artist and the record label did not agree as to which track to release as a first single. It was determined that SoundOut had to test the entire album, to collect more data to help resolve the problem. SoundOut conducted an experiment to test all 12 tracks of the album monadically in the US and UK markets with 400 consumers for each track. All responses were normalized and weighted based on the previous reviewing patterns of each reviewer and using the patented algorithms. This enabled each track to be rated on a 0–100% percentile scale both by demographic and by country, facilitating a clear side-by-side comparison of each of the 12 tracks. SoundOut were asked to meet with the band and present the findings of the research, managing to persuade them that their chosen single was not likely to be successful from a commercial point of view. Consequently, the label released the selected single that later achieved the first position in the UK charts.

Now consider another example, this time a US-based technology company, valued at over $10 billion, was planning a major radio campaign across several European markets to promote their service and needed to find a different actor to provide the voiceover for this campaign. SoundOut tested 10 different voiceovers (actors) for each of the target markets with over 400 consumers in each market to establish which voice most closely matched the core brand values of the client. The analytics SoundOut applied were able to quantitatively measure the % emotional match between each actor's voiceover and the client's core brand, identifying the one in each market that was most appropriate. The client used the results to select the actor in each market that best communicated their emotional brand values while delivering their advertising message via radio advertisements.

RORPs can also provide indirect benefits to the innovation process, as illustrated by the sixth case. The outbreak of COVID-19 has rendered a lot of research and development activities before launching a new product more complex and difficult. For instance, before the pandemic, designers, merchants, brand managers, and marketing leads would hold line review meetings, physically gathering to review the new item candidates, often bringing physical samples to the meeting. COVID-19 restrictions have pushed companies to undertake remote reviews which are facilitated by remote working platforms such as Teams or Zoom. However, these seem not to work effectively since someone had to get the physical samples and hold them up for all to see online. This situation promoted the need for "digital line reviews" which are enabled by RORPs. Since the RORPs can have high-quality photos or rotating 3D CAD images for the options, along with the consumer feedback, all in one screen, RORPs are being used as the primary remote meeting presentation tool. Further, participant comments and decisions can be logged in real time.

Four other RORP-usage trends have emerged during the COVID-19 pandemic: 1) an increasing demand to test items in growing categories such as home improvement, casual wear, and outdoor activity products; 2) a growing demand to test items from firms that are trying to find new, "whitespace" customers; 3) an increasing need to test from firms facing excess inventory of unwanted product (e.g., formal apparel, suiting); and 4) a focused demand from firms who need to test ways to reduce their assortment offering. An illustrative example of this last situation is one of the world's leading marketers and licensors of branded footwear and apparel. While this client has been using First Insight's predictive analytics for several years, they have understood that the COVID-19 pandemic has pushed consumers to buy fewer, but better products. Accordingly, the company is using First Insight increasingly to make sure which product can tick multiple boxes including style, durability, color, price, etc. This clearly benefits the manufacturer, but also the retailers, besides the consumers.

5. Discussion, contributions and implications

In this section we discuss our findings by illustrating how RORPs operate, and by generating a set of research/theoretical contributions and practical implications.

5.1 How RORPs operate

Based on our research on RORPs, we identified three key processes that, together, illustrate the operation of RORPs.

Design and deploy a digital experiment. In contrast to IORPs and TORPs, RORPs have to trigger the generation of ORs either by soliciting digital feedback via targeted invitations (emails, social media postings, etc.), or by creating *ad hoc* digital markets labs wherein testing of new products and services can take place, i.e., RORPs have to design and deploy an appropriate *digital innovation experiment*. Test authors and development processes vary by RORP, from self-service SaaS models to "high touch" consultative models. Interestingly, the digital innovation experimentation carried out by RORPs is distinct in at least ***three ways*** from the traditional online/offline innovation experiments conducted by companies and those found in previous online experimentation studies (e.g., Kohavi and Thomke, 2017; Thomke, 2020).

First, the scope of RORPs' innovation experiments tend to be significantly wider than IORPs and TORPs, rendering them more complex and the findings potentially more insightful. For example, most existing digital innovation experiments involve univariable A/B or A/B/n tests, whereby the modification/s of a feature of a product, service, or business model is/are carried out to identify the best-performing variation/s compared to the control (with A being the control, the status quo of the product/service/business model, and B, C, … 'n' being the variations). A few very recent studies have also reported how some companies are engaging in A/B testing (Kohavi and Thomke, 2017). However, while analytical techniques such as conjoint analysis can test multiple variables, they are not scalable beyond a limited number of variables, and take lots of time and effort on the respondent's part. Our study shows that RORPs' experiments, instead, encompass more complex multivariate tests that evaluate multiple modifications across different features simultaneously (for example, the timbre of the voice of a singer, the genre of music, the style of singing, the volume of each instrument, the style of singing, etc. within the music sector; the style, design, color, shape, etc. in the apparel sector) and over time (i.e., longitudinal). The test can be made extremely realistic as 2D and 3D CADs can be the object of the test.

Second, the subjects for RORPs' innovation experiments can be crowdsourced from small or very large panels (typically in the order of millions), from across the world, in real time. Further, as these subjects (potential customers and panel members) have either been working for the RORPs over a long time (normally 4–5 years or even more), or have a knowledge of similar products to those tested, their OR ratings and text analytics can be normalized based on previous reviewing patterns and weighted based on how representative they are of the client's targeted demographic (in each product category). Thus, it is possible for some RORPs to track the history of each individual reviewer longitudinally, and (i) drop from an experiment subjects whose past reviewing activity does not comply with the quality standard/threshold set by the algorithms, and (ii) create time-series experiments with only high-quality reviewers. The most advanced RORPs apply the principle of quality over quantity in terms of consumer panels: it is more important to select consumers that are "in the know" (e.g., those who are more knowledgeable about the product being reviewed) as testers, rather than assembling a large panel of consumers who have no knowledge of or experience with the product category. This results in a focus on the signal (leading from data to information to knowledge) and elimination of any noise in the data.

Third, RORPs' testing tools rely on data mining techniques, predictive analytics, and machine learning algorithms that (1) check the quality of ORs (and generally on-line responses) and (2) analyze the data to provide results, some based on predictive analytics. Quality of inputs can be based on a number of factors (e.g., time spent to write the review, length of the review, diversity in the text, relevance, quality of language, plagiarism, etc.). In some cases, Bayesian modeling is used to select the most suitable respondents (i.e., customers who know what worked well in the past and are likely to know what will work in the future). This again allows RORPs to retain only high-quality reviews and ensures the overall rigor of the innovation experiment. Results and recommendations can be analyzed with machine learning and predictive analytics algorithms in isolation or combined with other data, such as actual in-store performance. In some cases, machine learning is used to build predictive algorithms for future related experiments for the client firm.

For example, First Insight's SaaS solution enables users to create and deploy tests on their own, or with some guidance from a First Insight representative. They start by identifying the insight objective, or decision they are trying to make regarding the alternatives (e.g., combinations of features, design elements, technologies, pricing, etc.). Then, they enter the names, descriptions, image(s), and test price for the new product alternatives. They can add survey questions regarding demographics, psychographics, purchase behaviors, etc. to help segment results. Finally, they add reference items to the experiment to help filter and identify respondents who are "in the know" on the test item category. Such items enable First Insight's platform to improve predictive accuracy of results, while streamlining the number of required responses to 150–200. Experiments are then deployed to target panels who "play a game" on a web browser. Respondents can be solicited via a firm's CRM database, third-party panel providers, and social media postings. Incentives such as coupons or points may be offered, but are not required, depending on the source. Enough responses can be gathered in minutes to 24–48 hours.

In comparison, SoundOut relies on a team of data scientists to develop such an environment and to adapt it to the client's specific needs (be it a major record label, a fashion company, or a retailer). The actual crowdsourcing and retrieval of OR data is preceded by the administration of a new product or a service online to a large panel of reviewers. Reviewers are rewarded for their reviews based on algorithms that quantify the quality (or value) of the reviews (which allows allocating higher monetary rewards to high-quality reviewers/reviews). The ORs related to the new product/service are collected in real time and are endowed with metadata (e.g., timestamp, geo-location with latitude and longitude, etc.). Data are collected 24/7 as a flow, rather than in huge batches, and stored on cloud-based servers (e.g., SoundOut leverages Amazon Web Services).

Apply data analytic techniques. RORPs typically apply predictive analytics, semantics analysis, sentiment analysis, machine learning, and other technologies to the data set collected. The algorithms and data sets will vary by RORP. For example, First Insight analyzes the results in real time to determine if sufficient responses have been received from users "in the know" on the tested category. Once a valid sample set has been collected (typically 150–200 responses), predictive analytic algorithms are applied to compute results re: perceived item value, pricing, comments, sentiment, etc. in a matter of minutes.

In the case of SoundOut, the quality of ORs is assessed deploying machine learning algorithms that consider almost 50 factors (e.g., plagiarism, quality of language, relevance), and based on this, individual reviews are automatically rejected or accepted. If the database is proprietary, all ratings are normalized based on each reviewer's past behavior and their opinions weighted based on how representative they are of their demographic (in each category). The outputs are combined with actual in-store performance and machine learning is used to build predictive algorithms. This ensures the maximum accuracy in the predictive analytics generated. Data are processed in real time as "items" receive the target number of ORs using a host of proprietary algorithms. The analytics generated are both predictive, as they address the question "What will happen in the future?", and prescriptive, as they address the question "How to optimize processes in the future?". First Insight, SoundOut, and other RORPs employ a wide range of analytic techniques to generate predictive insights.

Report findings. SoundOut, First Insight, and other RORPs employ their own proprietary visualization platforms to present results to their clients. In addition, they may use a range of third-party visualization tools, such as Tableau and Shiny (to enable visualizations from R). Others may export results automatically to another enterprise system (e.g., PLM system, data warehouse, pricing optimization systems, assortment planning systems, CRMs, etc.) via an application program interface (API). Furthermore, by embracing cloud-based technologies and adopting a SaaS solution, RORPs allow their clients to access in real time both predictive and prescriptive analytics and insights based either on digital data streams or digital data stocks (Pigni et al., 2016).

To deliver the value articulated earlier, RORPs need to address a few key issues and challenges. First, the core value proposition of RORPs lies in their ability to predict customer preferences and the demand for products, but innovation also exists with services, solutions, packaging, branding, advertising, etc. across different industries. So, RORPs must be able to support experiments beyond tangible products. Second, their methods must support products with various life-cycles, from short cycles (e.g., music, fashion) as well as those with relatively longer cycles (e.g., toys, home décor, consumer electronics). As such, a key opportunity for

RORPs would be in evaluating and adapting their techniques and business models to help address innovation risks with diverse test subjects in diverse types of markets. Third, RORPs must align their processes and deliverables with contemporary innovation approaches such as digital product creation (DPC) and virtual manufacturing (Dépincé et al., 2007). Additionally, as lean product development approaches grow in increasing importance across industries, RORPs' ability to support rapid and iterative experimentation and validation present them with the opportunity to align more closely with industry standard innovation/entrepreneurial methodologies such as lean startup (Ries, 2011). Indeed, by generating insights for business model iteration and pivoting, RORPs can deliver transformational capabilities to innovators and entrepreneurs that go beyond mere open innovation (Chesbrough, 2003, 2019). Fourth, RORPs also need to place BDA and digital technologies such as AI at the heart of their business and strategies (Kaplan and Haenlein; 2019; Pillai et al., 2021; Tabesh et al., 2019). Unlike traditional views of open innovation that imply knowledge sharing and spillover, experimentally crowdsourced ORs in RORPs' digital innovation experiments are generated in a controlled and protected environment that is "relatively closed": this is key to protect the innovation knowledge deriving from innovation analytics and avoid knowledge leaks. Moreover, experimentally crowdsourced ORs constitute a more focused and tailored way of generating analytics than harvesting online content available on online forums (Kakatkar et al., 2020). Finally, this in turn implies that RORPs need to continually invest in renewing their related assets, resources, and capabilities. RORPs display very specific features in terms of digital experimentation and BDAC (Gupta and George, 2016) that make them distinct from IORPs and TORPs. We can term them *digital experimentation analytics capabilities*, which are displayed in **Table 2**.

[Include Table 2 about here]

For example, Virtual and Augmented Reality (VAR) technologies allow RORPs to conduct online experiments to test customer acceptance of features of physical products, thereby expanding the scope of their business to other industries (e.g., home appliances, auto, etc.). Further, given that the boundaries across traditional industry verticals become progressively more porous and blurred, there is a critical need for RORPs to understand industry-specific key performance indicators (KPIs), terminology, business processes, etc. in a more comprehensive way and to adopt analytical approaches that would enable them to address the question "Why would this new product or service be needed only within this particular market and not in adjacent markets?". More broadly, to deliver the promise of RORPs, data scientists working for RORPs will need to adopt capabilities to interpret data out of silos and across industry verticals.

5.2 Theoretical contributions

Our research makes several theoretical contributions. First, we contribute to the literature on ORPs and ORs (Cheung and Lee, 2012; Mayzlin et al., 2014) by developing a new typology of ORPs which enables us to extend previous work on ORs in the marketing field (e.g., Zervas et al., 2020) by advancing further the relevance of user-generated content and ORs in the innovation field (Kakatkar et al., 2020: Mariani and Fosso Wamba, 2020). In line with recent studies on innovation analytics (Kakatkar et al., 2020), our findings confirm that user-generated content can be useful to create value for innovation managers. However, we move one step forward and, by focusing on ORs as a specific form of user-generated content, and conceptualizing information-, transaction-, and research-driven ORPs, we are able to differentiate more subtly ORPs and characterize the type of business value that they create and the audiences to which that value is delivered.

Second, this work contributes to conceptualize a new and novel form of ORP: *Research-driven Online Review Platform* (RORP), that combines the science and rigor of very large-scale, low-cost, fast-paced, and complex digital experimentation using real-world customers on digital platforms with the power of modern AI-based BDAC to generate novel innovation insights. This type of platform is critical for any innovation initiative in a digital context. In this way, we extend previous work in innovation management within digital settings (Mariani and Fosso Wamba, 2020; Nambisan et al., 2017).

Third, we contribute to the research stream on online experimentation (Kohavi and Thomke, 2017; Thomke, 2020) by introducing the novel concept of digital innovation experimentation and suggesting that it can make a difference for organizations using Industry 4.0 technologies and developing an Industry 4.0 strategy (Santos et al., 2017). As recent systematic reviews of Industry 4.0 literature (e.g., Mariani and Borghi, 2019; Xu et al., 2018) have not identified digital innovation experimentation as a focal theme, we believe that our research contributes to enriching the conceptual scholarly debate revolving around Industry 4.0 by adding this further critical theme (i.e., digital innovation experimentation).

Last, we contribute to the fast-developing literature on BDAC (Gupta and George, 2016; Mariani and Fosso Wamba, 2020; Mikalef et al., 2018; Mikalef et al., 2020), suggesting that different ORPs require different BDAC and that digital experimentation analytics capabilities are not a homogenous construct, but differ across different types of platforms. More specifically, while Gupta and George (2016) find that three major types of resources underpin BDAC, we suggest that digital experimentation analytics capabilities require different mixes of these resources across different types of ORPs.

5.3 Implications for practice

It is becoming quite evident that with the increasing globalization of markets and the ensuing intense competition, companies have to become nimble and proactive in their innovation and entrepreneurial initiatives. Adoption of digital product creation and 'lean innovation' techniques by both established and new ventures illustrate this well. RORPs present a natural complement to such approaches and as such hold important implications for innovation managers (e.g., designers, product/brand managers, merchants, buyers, marketeers) and entrepreneurs. First, innovation managers and entrepreneurs should see RORPs as an asset for customer-centric innovation, able to trigger better performance and business results. While RORPs are one of the tools that companies can deploy to innovate in the digital age, in some cases they are perceived merely as an additional investment in R&D and therefore an additional cost. Some innovation managers and entrepreneurs think they know better than the market, or that their intuition is a good enough guide. However, as most of the projects conducted by RORPs show, the predictive analytics and insights generated by RORPs are conducive to high ROI and higher margins. For instance, in supporting the footwear company Hush Puppies, First Insight helped them to evaluate their potential portfolio of new items for the upcoming season. Through the application of predictive analytics on voice-of-the-customer inputs on potential new items, Hush Puppies managed to reduce the number of styles presented to retailers by 42%, while increasing the styles adopted by 88%. Pairs ordered increased by 39%, while pairs ordered per style increased by 29%. This all translated into happier channel partners and better financial results. These results would not be achieved without a customer-centric approach to digital experimentation. As suggested by a First Insight executive, the adoption of RORPs "implies a shift from seeing experimentation as a 'testing tax' that takes lots of time and effort, often for only a few select new options, to a desired, 'customer-on-my-shoulder' model for all key decisions." Accordingly, RORPs' clients should develop a customer-centric culture where the *voice of the customer* becomes the beating heart of any innovation initiative. Indeed, it is through analytics stemming from the *voice of the customer* that First Insight is able to predict if a product will be a hit or a failure, the price at which the new product should be sold, the right quantity of products to manufacture, and the type of customers to target.

Second, innovation managers and entrepreneurs should make RORPs part of the firm's internal innovation infrastructure. While RORPs offer promising opportunities for businesses to address some of the important knowledge gaps in their innovation projects by means of innovation analytics, businesses will need to adopt explicit strategies to embrace RORPs and make them an extension of their internal innovation infrastructure. For example, the value they can extract from RORPs is contingent on framing the appropriate questions for experimentation and testing. And, this in turn requires a close partnership between the RORP and the internal innovation team in determining the test objective and how to structure the test. Similarly, the output from RORPs (i.e., the innovation analytics derived from customer reviews or evaluations) has to be embraced and acted upon by the internal team and this in turn requires the adoption of an "open innovation" culture—one that is receptive to external inputs and suggestions. More broadly, to realize value from RORPs, innovation managers and entrepreneurs may need to make appropriate changes in their internal innovation structure and/or culture.

As an example, First Insight sees users in the design and development teams creating their own innovation research studies and providing the results to the product/brand managers, as well as the marketing team. This process is a change for many organizations where the leadership of such research is moving from consumer-insight and research teams to specific functional teams that have specific decisions that can benefit from specific customer inputs, and then sharing the feedback cross-functionally.

As the CEO of SoundOut noted, "We find that many clients know what they want to find out but struggle to frame questions in a way that will deliver those insights. As a result, we typically ask the client to tell us what the goal is, and we then design the questions that will deliver these insights. A major client in the fashion industry mentioned that they wanted to know which feature to prioritize in their spring collection of women's shoes and identify a recommended retail price. After receiving indication on the demographic group that the fashion client wanted to target, SoundOut conducted parallel experiments across the two countries with the same demographic group and showed the customers three styles with different colors." The insight that emerged from the experiment was that customers' willingness to pay for the three different styles in the two markets was a function of combinations of colors; accordingly, color was the crucial attribute to test.

Third, innovation managers should evaluate the appropriateness of RORPs for an innovation project. Before committing resources to configuring experiments or working with RORP representatives to do so, innovation managers and entrepreneurs have to carefully evaluate the appropriateness vis-à-vis the particular innovation project and context. Different types of market contexts present different types of innovation-related knowledge gaps and uncertainties and may call for different types of data analytics approaches. For example, as noted earlier, fashion-oriented markets typically have short life-cycles, are cyclical, and are prone to rapid changes in consumer tastes and preferences. As such, planning experiments for such markets would be markedly different from those for more stable markets. Further, the way to interpret results from RORPs' analytics may also be contingent on the nature of market context and related risks and uncertainties. Thus, innovation managers and entrepreneurs will need to carefully consider all of this before configuring or commissioning RORPs to conduct specific product tests. This in turn implies that they cannot really *outsource* the innovation experiment to RORPs. While some RORPs provide a self-service model, in some cases, innovation managers and entrepreneurs will need to *partner with RORPs* in devising and deploying appropriate innovation experiments. As the Senior Vice President of a RORP company shared with us: “Often lead times in fast fashion are relatively short but designers and buyers are often stocking in anticipation of a trend, one that consumers are not yet aware of or locked into.” One of their major retail clients mentioned that “When testing our items, we have been advised to test different interpretations of a trend rather than seek approval of the trend itself. This way we can still follow our trend strategy but ensure the execution of this is based on the best possible design.”

Fourth, innovation managers and entrepreneurs should shift the focus from functional risks to business risks. Innovation managers and entrepreneurs have to adopt a broader cross-functional perspective to really leverage the value promised by RORPs. Online customer reviews offered by RORPs are not meant to merely serve one or more marketing decisions (e.g., pricing); rather, they imply the opportunity to learn about new markets and consumer behavior and to fashion a company’s business model based on the novel insights derived from the RORP experiments and data analytics. This in turn implies that businesses will need to form an internal cross-functional team to interact with RORPs and to ensure that the outcomes from RORP tests inform the company’s overall business model (related to the new product or service) and are transformative. All of this is in contrast to the way in which businesses interact with traditional market research and marketing analytics firms, which often involve support in narrower and functional areas. For instance, some larger retailers have dedicated testing teams to act as an interface between the RORP and the internal business teams. As the data science lead of a RORP told us, “Our client’s testing teams act as a filter to collect, analyze, and then disseminate only relevant information to their innovation teams without swamping them with data, much of which will be of marginal commercial value and may simply confuse rather than improve their decision-making.” Overall, a RORP is a tool that promises to dismiss the

“Nobody knows anything” mantra on an increasing range of products and in multiple industries, much beyond the movie industry. Indeed, RORPs allow the crowdsourcing of experimental ORs to generate innovation analytics, enabling future demand to be predicted when data are absent.

Fifth and last, innovation managers and entrepreneurs should ride the wave of consumers’ digital platform adoption. Innovation managers are aware that the pace at which digital technologies are developing and diffusing is also co-determining an empowerment of digital innovation experimentation. Indeed, increased Internet penetration and speed in many geographical areas worldwide, ubiquitous mobile devices, and apps development are all factors leading to an increase of the means through which the voice of the customers can be embedded in any innovation process. The development of digital technologies has been further accelerated by the outbreak of COVID-19, and therefore digital experimentation will become increasingly important as it will become increasingly cheaper, faster, and more accurate than outdated offline research tools.

6. Conclusion and limitations

Companies across industries are seeking new avenues to accelerate the speed of their innovation and entrepreneurial initiatives while preserving their capability to be nimble to deal with dynamic global markets. The promise and potential of OR-based innovation analytics presented here, namely Research-driven ORs platforms and their role as a powerful tool for digital innovation experimentation, should be viewed in this context. RORPs bring strategic and transformational value to client companies by generating innovation insights through well-designed digital experiments that crowdsource meaningful ORs. At the same time, explicit complementary strategies and practices should be adopted on the part of innovation managers, entrepreneurs, and chief technology officers to guarantee that RORPs form a natural extension of a client company's innovation and entrepreneurial infrastructure. With such appropriate complementary strategies, RORPs can trigger truly transformative changes in companies and promote lean thinking in all innovation and entrepreneurial activities, thereby making the companies more competitive and successful.

We critically underline several potential challenges that need to be faced when engaging with RORPs. First, unlike traditional views of open innovation (Chesbrough, 2003, 2019) that imply knowledge sharing and spillover, RORPs' digital innovation experiments need to be generated in a closed environment: this is key to control and protect the innovation knowledge deriving from innovation analytics and avoid knowledge leaks. Opting for closed vs. open digital innovation experiments has different implications for value appropriation (Jacobides et al., 2006) stemming from innovation analytics. This implies that the stakeholders involved in the digital innovation experimentation should share a common view in relation to value appropriation. Second, as RORPs display very specific features in terms of digital experimentation and BDAC (Gupta and George, 2016) that make them distinct from IORPs and TORPs, the type of investment needed to renew their resources (tangible, intangible, and human) might be different compared to that of IORPs and TORPs. Future research might adopt a BDAC lens (Gupta and George, 2016) to shed light on the type of investment needed and its frequency. Third, while RORPs bring online experimentation (Thomke, 2020) to the next level as they align with innovation/entrepreneurial methodologies such as lean startup (Ries, 2011), the important insights for business model iteration and pivoting and transformational capabilities should be treasured to facilitate digital transformation processes (Gurbaxani and Dunkle, 2019) in firms that are not digital natives.

This study is not without limitations. First, while we analyzed a wide number of cases due to the novelty of the phenomenon examined (Eisenhardt, 1989), more cases might be needed to improve the generalizability of the findings, especially from non-Anglo-Saxon countries. Nonetheless, as ORPs in general and RORPs in particular operate in digital environments and are themselves digital platforms, we believe that the findings might hold across platforms regardless of the specific cases analyzed. Second, further research might develop research hypotheses to test quantitatively the differences across platforms that we have been able to qualitatively capture.

Future research might leverage more thoroughly the conceptual apparatus of digital entrepreneurship literature (Nambisan, 2017) to make sense of why entrepreneurial stakeholders use differently ORPs depending on situational circumstances to shape their entrepreneurial ecosystems. Second, and related to the previous point, scholars interested in digital business models (Keen and Williams, 2013; Weill and Woerner, 2013) might try to delve deeper into the features that platforms should develop to improve value generation architectures.

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Figure 1: Online review platforms and the audiences they serve

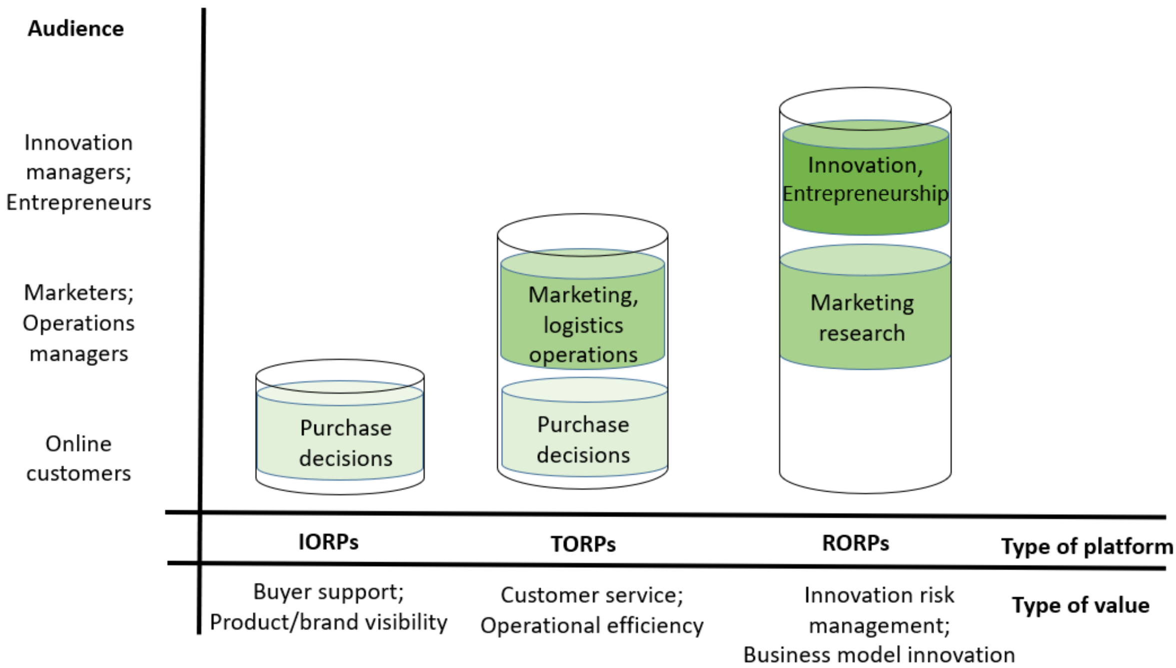

Table 1 – A comparison of the three types of ORPs

Type of ORP	Type of website	How ORs are generated and hosted	Why ORs are hosted and what kind of value they generate	How ORs data are used	For what purposes ORs data are used
Information-driven ORPs (IORPs)	Independent online review platforms; social networking websites; online phone directories; search engines	ORs are crowdsourced, written by registered users, and are visible to all Internet users. ORs relate to products/services not transacted on the platform. Reviewers are not rewarded by platform managers for their reviews. Algorithms and mechanisms to validate and/or evaluate quality of reviews may be available. Reviews primarily provide information to prospective buyers and guide their purchase decisions.	ORs are functional to the business of the company, i.e., to provide information about businesses and their products and services. ORs generate mostly **informational value**.	Potential customers read ORs posted by other reviewers. Platform managers can use data to profile their users (e.g., Facebook, Google).	Data are used by customers to collect information before purchasing decisions. Data are used by platform managers to profile and segment their users. Potentially, data might be used for user micro-segmentation and location-based marketing.

Transaction-driven ORPs (TORPs)	E-commerce websites; sharing economy websites	ORs are written by online customers after a verified purchase and are visible to all Internet users (and providers in sharing economy websites). ORs relate to products/services transacted on the same platform. Reviewers are often rewarded for their reviews. Most platforms employ mechanisms and algorithms to validate/authenticate reviewers/reviews and to provide quality-based filters. Reviews provide: (a) information to prospective buyers and guide their customer journey; and (b) critical insights to platform company managers on product popularity and guide their operational decision-making.	ORs are relevant for the core business of the company, which is to sell existing products and services via the e-commerce or sharing economy websites. Review valence and helpfulness seem to positively affect sales. ORs generate mostly **transactional value**.	Potential customers (and providers) read ORs posted by other reviewers (that can be both customers and providers). Platform managers can use data to profile their users, understand what products and services sell more, and encourage users to write reviews and company managers to respond.	Data are used by customers (and providers) to collect information before economic transactions. Data are used by platform managers to profile and segment their users, for location-based marketing, customer micro-segmentation, pricing, and distribution optimization. Data are used by companies' managers to incrementally improve the features of their products and services, optimize distribution, and manage inventory and capacity utilization.
Research-driven ORPs (RORPs)	Digital analytics platform	ORs written by individuals who are specifically recruited as "product testers", and the reviews and accompanying analysis are visible only to the client company. ORs relate to products/services that have not yet been launched. Reviewers may be rewarded for their reviews. Sophisticated set of mechanisms and algorithms ensure the authenticity of reviewers/reviews and the quality of reviews. Analysis of OR data generates critical insights on the market potential, pricing and distribution of a new product/service.	ORs are critical for the core business of the digital analytics platform, which is to generate data analytics-based insights for client companies about the online market potential of a new product or service by testing it and quantifying customer satisfaction. ORs generate mostly **strategic and transformational value**.	Platform managers and their clients deploy data to generate analytics that can be used by business customers for their R&D, marketing, production, and supply chain activities.	Data are used by platform managers to generate both predictive and prescriptive analytics. Platform services (often in the guise of test results) are sold to business clients that use them to: test new products and services before release; forecast demand for new products; carry out assortment optimization; implement customer micro-segmentation; carry out multi-channel marketing; and make pricing decisions.

Table 2 – Features of digital experimentation and digital experimentation analytics capabilities across the three types of ORPs

Type of ORP	Type of website	How digital experimentation is carried out and why	Digital experimentation analytics capabilities
Information-driven ORPs (IORPs)	Independent online review platforms; social networking websites; online phone directories; search engines	While some of the IORPs (e.g., social networking sites) conduct thousands of controlled experiments annually, they are aimed at understanding how their users engage with the platform and testing the usability of the platform itself, rather than at testing new products/services outside of the platform (see the experiment that Facebook carried out in 2012 on 690,000 users to understand if emotional states were contagious on its platform). Algorithms might be developed to increase the engagement of the users with the platform, thus giving more visibility to ORs that cover the platform in a positive way.	***Tangible resources***: Data are the result of a spontaneous reviewing behavior of platform users. For this, IORPs need to develop and maintain the technology of the platform, which can be expensive if the only aim of the company is to significantly enhance users' engagement with the platform (e.g., SNS vs. online phone directory). ***Human resources***: In terms of *managerial skills*, platform managers can use data to profile their users (e.g., Facebook, Google) to improve their advertising services (e.g., Facebook Ads, Google Ads). The *technical skills* sitting in IORPs can make a difference in retrieving, processing, analysing, and reporting data that can be used to improve users' profiling. ***Intangible resources***: Not all the IORPs display the same data-driven culture. For instance, search engines (e.g., Google) and social networking websites (e.g., Facebook) have a well-developed data-driven culture and run thousands of controlled experiments annually to improve their platforms. The same does not necessarily apply to online phone directories. The intensity of *organizational learning* is variable across IORPs.

Transaction-driven ORPs (TORPs)	E-commerce websites; sharing economy websites	Most of the TORPs (e.g., e-commerce websites) conduct thousands of controlled experiments annually, to improve the website in terms of usability, enhance online customers' experience, and increase conversions. Testing is confined to testing the usability of the platform itself and generating insights on products transacted on the platform and covered by a review written by a verified purchase, rather than related to testing new products/services outside of the platform (see the experiments carried out by Booking and Amazon). Algorithms might be developed to improve the customer journey on the website, reduce bounce rates, and increase conversions. Moreover, the platforms deploy several algorithms to support prospective buyers' decisions and guide their customer journey, for instance through filters of online reviews by helpfulness votes and language/country of origin of the customer.	***Tangible resources***: Data are the result of spontaneous reviewing behavior of platform users after a verified purchase. For this, TORPs need to constantly develop their technology and develop the platform and the underlying algorithms (e.g., ranking of online reviews by helpful votes), and commit a relevant amount of basic resources (time and investment) to significantly enhance users' experience, journey, engagement, and purchase intention. ***Human resources***: In terms of *managerial skills*, platform managers can use data to profile their users, understand what products and services sell more, and encourage users to write reviews and company managers to respond. The *technical skills* sitting in TORPs can make a difference in retrieving, processing, analysing, and reporting data – by means of data-driven techniques – that can be conducive to *marketing analytics*. ***Intangible resources***: All of the TORPs display a highly advanced data-driven culture. For instance, e-commerce websites (e.g., Amazon) and sharing economy platforms (e.g., Uber) have a well-developed data-driven culture as the platform managers make decisions based on analytics that need to be communicated to their counterparts (marketing experts in client companies/brands) who also have a data-driven culture. The intensity of *organizational learning* for TORPs is high (especially in testing the usability of the platform).
Research-driven ORPs (RORPs)	Digital analytics platforms	All of the RORPs have digital experimentation as their core business. They conduct a very high number of controlled digital experiments involving individuals who are specifically recruited as product testers, with the aim of crowdsourcing high-quality online reviews of new products and services to generate innovation insights. The online reviews and accompanying innovation insights are visible only to the RORP and client company, which uses the insights to forecast	***Tangible resources***: Data are the result of a controlled digital experiment. Digital test items are often created using digital design tools. Use and integration with other systems (e.g., PLM, CAD, CRM, Data Warehouse, etc.) may take place. The protection of the experimental environment allows innovators to protect innovation analytics. For this, RORPs need to constantly develop their technology and invest in AI and ML infrastructure. Moreover, they develop the platform and the underlying algorithms (e.g., algorithms checking the quality of reviews and reviewers), and commit a relevant amount of basic resources (time and investment) to significantly enhance the predictive power of their innovation analytics.

	demand and determine the prospective consumers' willingness to pay for a new product before its launch (as well as the entry price). Testing is the value proposition (i.e., products, services) of the RORPs and testing is applied to everything, including new products and services.	***Human resources***: Training regarding the right business question and hypotheses to test is typically required, with guidance to the innovation manager of the client company (e.g., manufacturer, retailer) by the RORP optionally available. The technical skills in the RORP come in the form of industry knowledge, analytics knowledge, and data science skills, all of which can make a difference in designing, executing, and obtaining the results through retrieval, processing, analysis, and reporting of the data – stemming from the voice of the customer – that are conducive to *innovation analytics*.
	Algorithms are developed to forecast demand and determine the prospective consumers' willingness to pay for a new product before its launch. The innovation analytics are used to generate critical insights on the market potential, pricing, and distribution of a new product/service. Moreover, the platforms employ several algorithms to support the generation of high-quality and predictive analytics. These algorithms also ensure the authenticity and quality of reviewers/reviews.	***Intangible resources***: The RORP displays by default a data-driven culture and should encourage also its client to espouse it. The more a client (e.g., manufacturer, retailer) collaborates with a RORP, the more they acquire a data-driven culture for innovation. The intensity of *organizational learning* for RORPs is extremely high because they have not only to keep pace with data analytics in general, but also create new metrics and algorithms to address the need of high-quality data for innovation analytics and the experimentation and innovation needs of the client.