Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis

Published Version:
Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis / Pantano, Eleonora; Pizzi, Gabriele. - In: JOURNAL OF RETAILING AND CONSUMER SERVICES. - ISSN 0969-6989. - ELETTRONICO. - 55:(2020), pp. 102096.1-102096.9. [10.1016/j.jretconser.2020.102096]

Availability:
This version is available at: https://hdl.handle.net/11585/770395 since: 2020-09-07

Published:
DOI: http://doi.org/10.1016/j.jretconser.2020.102096

Forecasting artificial intelligence on online customer assistance: evidence from chatbot patents analysis

Abstract.

The main goal of this research is to provide a comprehensive understanding of the actual progresses in artificial intelligence, with emphasis on chatbots as emerging forms of customer assistance in online retailing. Drawing upon an analysis of the chatbot patents in the past 20 years, our findings show the increasing technology push towards the adoption of new conversational agents based on natural language. Findings also highlight the extent to which the research and development efforts are attempting to improve artificial intelligence systems that characterize chatbots. To this end, technology advancements are mainly focusing on: (i) improving chatbot ability to automatically draw inferences on users starting from multiple data sources, and (ii) using consumers' knowledge adaptively to provide more customized solutions. Finally, results show the tight relationship between the digital assistants' analytical skills and their ability to automatically interact with the users.

Keywords: online customer assistance; artificial intelligence (AI); chatbot; patent analysis; online retailing; conversational agents

1. Introduction

Popular social media such as Facebook and Twitter are increasingly being used by retailers as a channel for providing assistance to customers through dedicated personnel (Demmers, van Dolen and Weltevreden, 2018). However, flash-and-bone employees might be replaced by virtual assistants as chatbots to provide 24/7 assistance at lower costs rather than human assistants. Although the idea of "virtual agent" dates back to early 2000s (Lai, 2000), the recent technological advancements in artificial intelligence (AI) allow the development of new and more efficient virtual assistants (online chatbots). Indeed, these systems are able to mimic human language/conversations and provide more realistic experiences (Lai, 2000; Hill, Ford and Farreras, 2015; Mou and Xu, 2017). Not surprisingly, the chatbot industry is expected to follow a double-digit growth rate in the next five years, reaching 1.25 USD billion by 2025, growing at a CAGR of 24.3% (Grand View Research, 2017). The investments in this sector are driven by the more successful integration of the technology in retail process to provide higher customized services, supported by the better understanding of consumers' preferences and behavior (Grewal, Roggeveen, and Nordfält, 2017; Huang and Rust, 2017; Papagiannidis et al., 2017).

Past studies largely focused on how humans converse with robots (Hill, Ford and Farreras, 2015; Mou and Xu, 2017), or how chatbots might replace human jobs (Huang and Rust, 2018), while research analyzing how the progresses in technology in terms of new chatbots would impact on the future customer assistance is still scarce, especially in retail settings. Indeed, technological innovation in AI is enabling chatbots to address increasingly complex tasks thanks to the application of holistic thinking and context-specific responses (Huang and Rust 2018). Nevertheless, there still seems to be a time gap between what AI might potentially do and its actual implementation. Accordingly, some research revealed that AI awareness has only a 50% probability of being achieved by chatbots by 2050 (Müller and Bostrom 2016). Despite the various progresses made in the recent decades, chatbot technology still in the midst, by indicating many directions for future development (Arsovski, Wong and Cheok, 2018).

In retailing, knowledge push has been evaluated through the analysis of patented innovations in order to make prediction of the critical areas of development and technological trends the sector (Pantano et al., 2017; Pantano, Priporas and Stylos, 2018). Nevertheless, the actual innovation research in online retailing shows a lack of investigations on how chatbots would affect the online customer assistance (Belavina, Girotra and Kabra, 2017; Bell, Gallino and Moreno, 2017; Bozer and Aldarondo, 2018; Chakraborty, et al., 2016).

Accordingly, the aim of this research is to provide a comprehensive understanding of the actual progresses in technology, with emphasis on chatbots as artificial intelligence systems. To this end, the research focuses on patent analysis as mean to evaluate the innovation trends and the technology push in online retailing in general and within the digital consumer assistance in particular. Drawing upon patent analysis, the study contributes to online retailing and retail management theory and practice by offering an overview of current/future applications of AI in customer assistance along with future trends, and mapping the main areas that these technologies might affect. In this way, findings would be beneficial to retailing, which needs to monitor technological changes and understand the innovative forces to maintain business profitability (Lee, Jeon and Park, 2011; Pantano and Vannucci, 2019).

The paper is organized as it follows: the next section will focus on customer assistance and chatbots as digital assistance agents. The subsequent one will introduce the methodology of research and the main findings. Finally, the implications for marketing and retailing theory and practice are discussed.

2. Theoretical background

2. 1 Customer assistance

Automation is increasingly becoming of paramount importance in retailing and, more generally, in the service domain (Rust and Huang, 2014), radically impacting the way consumers interact with companies (Bitner, Brown and Meuter, 2000; Chang, et al., 2016; Verhagen, et al., 2014). As a consequence, consumers interaction with retailers is shifting from personal assistance by flesh-and-blood employees to automated digital assistants, which help customers either online and offline with product- or service-related information (Felfernig, et al., 2006). Compared to the traditional brick-and-mortar stores, online settings are characterized by the possibility to develop automated and interactive tools to assist customers that might experience difficulties in shopping without the assistance of salespeople (Yoo, Lee, and Park, 2010). Despite the absence of a direct interaction with a personal assistant, digital agents offer the opportunity to combine the best features of each channel into one single shopping experience: the knowledgeability of assistants sought by consumers in the offline channel (Burke, 2002), and the customizability of the service in the online channel (Park and Kim, 2003).

The benefits of interacting with a digital assistant are both functional (i.e., time saving and efficiency in the purchase decision) (Yoon, et al., 2013), and social (i.e., the pleasure derived from the direct interaction with the firm, and the perception of being important for the company) (Holzwarth, Janiszewski, and Neumann, 2006). As a consequence, the critical issue consists of the quality of the virtual interaction that generates value for the customer as long as the assistant is able to fulfill the specific purposes it is aimed for (Mimoun, Poncin, and Garnier, 2017). In this vein, Huang and Rust (2017) distinguished between relational and transactional technologies that can fulfill either standardization or customization purposes. Among the formers, for instance, self-service technologies, robotic services or collaborative filtering allow to improve the efficiency of quite standardized activities that fulfill a given set of customer needs; among the latter, relational technologies, such as learning technologies and Artificial Intelligence (AI) are able to adaptively interact with customers (Huang, and Rust, 2017).

Accordingly, the extant literature argued that the consumer-company interface is rapidly evolving toward a technology-dominant logic where intelligent assistants act as the service interface (Larivière et al., 2017), and enable quicker and more effective decision processes by consumers (Satzger, Endres and Kießling, 2006). Correspondingly, a large deal of literature has been devoted to the identification of the relevant gaps that might hinder the full exploitation of such an automated customer assistance, such as the way the assistant appears (Araujo, 2018), the degree of "intelligence" (Ariely, Lynch and Aparicio, 2004), autonomy in understanding consumers' language (Mimoun, Poncin, and Garnier, 2012), and the extent to which their language and approach should vary across cultures (Culley and Madhavan, 2013). These studies solicit the identification of the features that assimilate digital assistants to natural user interfaces that can provide customers with accurate and timely recommendations, thus enabling companies to nurture the relationship with the customer (Lee and Choi, 2017) and minimize the distance between customers' expectations and agents' performance. Despite these contributions, a deeper understanding and anticipation of the supply side of the relationship seems to have been almost neglected in the scholarly agenda.

2.2 Chatbots as digital assistance agents

Digital agents have been defined as "computer-generated graphically displayed entities that represent either imaginary characters or real humans controlled by artificial intelligence" (Choi, Miracle, and Biocca, 2001, p. 19). Such a type of digital assistants can take different forms that range from interactive avatars (Keeling, McGoldrick, and Beatty, 2010), animated pictures (Zanker, Bricman and Jessenitschnig, 2011), or human-like animated agents mimicking a real salesperson (Verhagen, et al., 2014; Aldiri, Hobbs, and Qahwaji, 2008). Regardless of the specific form taken by the assistant, conversational agents have in common their representation of a personified entity that actively interacts with users in a knowledgeable way, and helps them to achieve their goals (Zanker, Bricman and Jessenitschnig, 2011), using consumers' natural language as input and providing natural language as output (Griol, Carbó and Molina, 2013).

Previous literature has addressed the role of other forms of technology-based customer assistants such as recommender systems based on collaborative filtering (Mimoun, Poncin and Garnier, 2012) or content-based filtering (Felfernig et al., 2014). More recently, conversational agents have acquired the interest of scholars and practitioners due to more functions (De Keyser et al. 2019; Luo et al. 2019). Indeed, the main difference between recommender systems and conversational agents lies on the fact that the latter stimulate a feeling of social presence/engagement that contributes to building trust among shoppers (Keeling, McGoldrick, and Beatty, 2010; Potdar, et al., 2018). This ability is driven by the higher level of involvement facilitated by an interaction able to stimulate also the affective and emotional side of the relationship (Choi, Miracle and Biocca, 2001).

Previous literature has also focused on multiple features of virtual agents and their impact on the virtual interaction with the customer. Some of these features are related to the way the digital assistant looks like such as gender (Beldad, Hegner and Hoppen, 2016), non-verbal behaviors such as eye gaze (Admoni and Scassellati, 2017) and gestures and movement (Castro-González, Admoni and Scassellati, 2016) or body language (Beck et al., 2013), and other human factors embedded in the digital assistant (Saunila, Ukko, and Rantala, in press.).

Research found that the more agents display human-like characteristics and behaviors, the more customers will be willing to relate with the digital assistant (Wilson et al. 2017). However, recent studies have highlighted that much research is still needed to investigate how technology should integrate these features in order to maximize consumer perceptions of trust and acceptance of conversational agents (Wirtz et al., 2018). For instance, human-like agents were found to be more effective in the virtual environment (Qiu and Benbasat, 2009; Mathur and Reichling 2016), since anthropomorphism well embodies the human characteristics that denote interpersonal relationships (Go and Sundar, 2019). Accordingly, other studies raised attention on the standards of verbal and nonverbal communication styles that are subject to cultural differences that might hinder their universal usability (Culley and Madhavan, 2013), such as the use of humor (Tay et al., 2016).

Similarly, Nowak and Rauh (2008) pointed out that too much anthropomorphism can backfire, since it might generate exaggerate expectations that, being hard to be met, might therefore translate into lower satisfaction evaluations. Other studies, instead, addressed the role of product category, and suggested that customers' reliance on conversational agents depends on both the level of risk they engage with the product category, and their previous knowledge about the product (Swaminathan, 2003). Prior research has further documented that the online environment is characterized by intrinsically higher levels of perceived risk that can be mitigated by means of appropriate and credible information (Flanagin et al., 2014). Furthermore, the higher level of perceived risk is typically associated with the higher need for extensive information search during the decision making process (Mitra, Reiss and Capella, 1999). Therefore, both the information provided by the digital assistant and the way it appears are relevant to the customers. Under this perspective, the online channel is characterized by a massive amount of information available to consumers during the entire path to purchase (Willems et al., 2017). Thus, the arising question on the optimal amount and type of information the digital agents should provide is worth of investigation.

2.3 Artificial intelligence and new avenues for digital assistants

AI can be referred to as "programs, algorithms, systems and machines that demonstrate intelligence" (Shankar 2018, p. 6), which resemble "intelligent human behavior" (Syam and Sharma 2018, p. 136). It actually relies on a set of tools such as machine learning algorithms, natural language processing, rule-based expert systems, neural networks, deep learning, physical robots, and robotic process automation (Davenport 2018), which help consumers simplifying the information provided on webpages (Sivaramakrishnan, Wan and Tang, 2007), by facilitating processes following the mental structures that define the customer's decision making process (Murray and Häubl, 2009).

The notion of information overload (Jacoby, 1977) is well rooted in the marketing literature suggesting that too much information can be overwhelming to consumers, depending on the type of product and the specific phase in the decision making process (Hostler, et al., 2011). For this reason, research has largely investigated how to best understand individual preferences in order to improve the capacity of digital agents to provide the type and amount of information that best fits each customer's need (Bodapati, 2008; De Bruyn, et al., 2008; Van Den Broeck, Zarouali, and Poels, 2019). Such consumers' preferences can be even elicited or interpreted by the digital agents themselves, by engaging the customer in multiple cycles of information exchange. In this way, the feedback obtained at each stage consists of a customer preferences estimation (Mcginty and Smyth, 2006). Similarly, data mining algorithms are able to classify the customer into a group of similar existing customers to make more efficient estimations and predictions (Griol and Callejas, 2016). Since the perceived fit between agents' recommendation and users' needs has been acknowledge as one of the most powerful sources of persuasiveness (Gretzel and Fesenmaier, 2006), past studies have contributed to stimulating the improvement of the agents' ability to interpret and respond meaningfully to human language (Hill, Ford and Farreras, 2015; Shah et al., 2016), With these regards, Davenport and Kirby (2016) distinguished between the digital assistants' task automation and context awareness. The former relies on standardized (or rule based) AI applications which entail the definition of logical rules in advance (Davenport et al. 2020). Conversely, context awareness requires machines to "learn how to learn", thus extending beyond the initial programming made by humans.

Accordingly, a rich stream of research and technological innovation is attempting to push AI to achieve superior capabilities in terms of analysis, understanding, and prediction (Ghahramani 2015). In this vein, neural conversational agents can be seen as a potential advancement in the ability of machines to learn the natural language used by consumers and to behave accordingly (Almansor and Hussain, 2019), by exploiting techniques such as Sequence to Sequence (Seq2Seq), Long Short Term Memory (LSTM) and Neural Network framework (Arsovski, Wong and Cheok 2019). Indeed, traditional chatbots are still characterized by a scarce intuitive ability to make a sense out of the meaning and set of relationships between words in natural language. As a consequence, they are still more suitable for direct question-answer exchanges, rather than for understanding users' reactions and assessing how the relationship is evolving (Chakrabarti and Luger, 2015), based on a "personalization without interrogation" approach (Murray and Häubl, 2009). To this end, AI seeks to simplify communication between humans and machines by means of natural language. However, given the complexity of human language, AI researchers are striving for new models that help understanding individuals' language (Almansor and Hussain, 2019). With these regards, Deep Learning (DL) qualifies as an appropriate tool to provide digital assistants with the ability to extract meaning from consumers' sentences, and generate the output consistently (Arsovski et al. 2019; Chatterjee et al. 2019). The major challenge in this domain is to empower algorithmic decision making, enabling digital assistants to act as gatekeepers (Andrè et al. 2018). This challenge involves how to effectively combine the input in individuals' natural language and the output in the machine's language (Nuruzzaman and Hussain 2019). Moreover, new technological improvements might potentially overcome the general skepticism and resistance exhibited by customers when interacting with conversational agents (Araujo, 2018; Fryer, Nakao, and Thompson 2019).

3. Methodology of Research

3.1 Research Design

Prior studies on technological innovation focused on patents analysis, due to the patents' unique trait of effectively reflecting innovation and synthetizing the evolution of technology towards a certain area of interest (i.e. sectors/industries, countries, etc.) (Pantano, et al., 2017; Pantano, Priporas and Stylos, 2018; Alfano, Pagnotta and Pantano, 2011; Chang, 2012; Kim and Bae, 2017). Park and colleagues (2005) defined the patent as a "source of technical and commercial knowledge about technical progress and innovative activity" (p. 473). Specifically, patents are documents describing the technical features of an invention, criteria for claiming originality, the market attributes, information about the inventor technical feasibility and commercial value. They further synthetize the proprietary and competitive dimensions of technological evolutions. In other words, patent is a document including the bibliographic data (including applicants, inventors, classifications, date of publication and abstract), description (including field of the invention, background of the invention, and detailed description), claims, drawings, original document, citations, legal events and patent family. Accordingly, past studied argued that patent analysis is a reliable mechanism for evaluating the level of innovation and technological development within a sector (Abraham and Moitra, 2001; Nelson et al., 2014). For these reasons, literature shows the large usage of patent analysis in different sectors, such as in the agri-food industry to evaluate farm-level innovation and develop an agricultural innovation index (Lapple, Renwick and Thorne, 2015), nanomechanics to evaluate the innovativeness of the systems used for the mechanical characterization of materials at the micro and nanoscale (Alfano, Pantano and Pagnotta, 2011), family businesses to evaluate the effect of technology push for family firms (Block et al., 2013), and so on.

Text mining techniques and bibliometric analysis (i.e., the number of patents in a certain period of time) are mainly employed methods to analyze patents (Lee, Jeon, and Park, 2011). Indeed, previous studies focusing on patent analysis largely used bibliometrics to identify the innovation trends (i.e., through the evaluation of the number of patents per year, as in Pantano et al., 2017). Patent analysis approach is specifically efficient in the exploitation of a large amount of data, allowing for the identification of patterns and prediction of future trends drawing upon historical data and trends (Pantano, Priporas and Stylos, 2018; Daim, et al., 2006). In particular, this approach allows the exploitation of a large amount of historical data as the number of granted patents, which can be explored to identify extant patterns and predict future trends (Pantano, Priporas and Stylos, 2018).

The present research is based on the collection of patents, evaluated though the textual analysis of the abstracts. This procedure allows automatically transforming patent documents into structured data to identify specific thematic areas and current trends understanding. To this end, the present research adopts the approach proposed by Lee et al. (2009) and Pantano, Priporas and Stylos (2018) to use text mining to deeply identify the thematic patterns within each patent document.

3.2 Data Collection and Procedure

The patents for the present analysis have been collected through the platform Orbit (and the devoted comprehensive database of all granted patents). In particular, the platform provides the query to select all the patented innovation related to a certain keyword in a specific period of time. We limited the selection to the patents including the words "chatbot" in the title and/or abstract, for a period between 1998 (first date of publication of a patent in chatbot) and 2018 (May). This period was considered suitable to provide a good overview of patent development over the last 20 years. This procedure yields the identification of 668 patents distributed across the international classification categories. The initial dataset for each patent has built included patent number, patent title, patent abstract, application date, acceptance date, assignees (patent owners), domain and country. Figure 1 shows the distribution of the collected chatbot patents across the different domains (according to the international classification categories), by emphasizing the major number of patents falling into computer science domain, then pharmaceuticals, digital communication and IT methods for management (colored darker in the figure). These results highlight the availability of systems that would potentially impact marketing in terms of amount and capabilities of new digital assistance (i.e., new form of communication/interactions between consumers and retailer).

Figure 1: The distribution of the collected 668 chatbot patents across the different domains.

WordStat software was further employed to explore the content of each patent and understand which aspect of the (online) customer assistance might affect. The choice of this software is explained by the proven robustness of results in research across different disciplines (Silver, 2004), and its ability to interpret textual data (as the contents of each patents abstract) through the identification of significant concepts (topics included in the patents abstract) and groups of concepts (phrases), thus supporting the objectivity, the replicability and the generalizability of the research methodology and findings (Davlembayeva, Papagiannidis and Alamanos, in print).

The first analysis consisted of the investigation of occurrences (the most frequent words, see Figure 2 in Findings). Secondly, the software allows the further extraction of topics and phrases, as the identification of idioms and themes recurrent in the text corpus (patent abstract), through built-in algorithms. These algorithms (i) scan the entire text corpus (consisting of all the patents abstract), (ii) classify the most frequent topics (Table 2), and (iii) identify the most frequent phrases (Table 3), which consist of the words association with a meaning as available in the "categorization dictionary" already included in the software. Since some words might be rarer than others but equally more predictive, it is necessary to weight them more heavily. To this end, the algorithm is based on the formula (1) to adjust the infrequently occurrence of words as (Humphreys and Wang, 2018), when

considering *tf* as the total frequency, and *idf* as *i* word in the document *d* (part of *D* total documents) frequency:

$$tf \cdot idf = [1 + \log(\text{number of occurrences of } word \text{ } i\text{n } d) \times \log \left(\frac{\text{total number of documents in } D}{\text{number of documents containing } w}\right)]$$

(1)

Thirdly, the final analysis performs the hierarchical cluster analysis and multidimensional scaling, representing those results through the dendrogram. Dendrogram is a tree graph, where the vertical axis represents the items and the horizontal one represents the clusters built during each step of the clustering process. In this way, it supports the graphical identification of clusters as word categories (Figure 2). In other words, the system uses an average-linked hierarchical clustering method to identify clusters from similarity matrices. The dendrogram is based on the Jaccard’s similarity coefficient (Seifoddini and Djassemi, 1991).

4. Findings

Table provides the list of occurrences (the most frequent words) as result of the first analysis.

Table 1. Identification of the occurrences.

	FREQUENCY	%SHOWN	% PROCESSED	% TOTAL	NO. CASES	%CASES	TF • IDF
USER	933	4,16%	2,16%	1,13%	260	38,92%	382,3
INFORMATION	604	2,69%	1,40%	0,73%	168	25,15%	362,1
SYSTEM	448	2,00%	1,04%	0,54%	216	32,34%	219,7
DATA	435	1,94%	1,01%	0,53%	136	20,36%	300,7
DEVICE	435	1,94%	1,01%	0,53%	166	24,85%	263
METHOD	383	1,71%	0,89%	0,46%	254	38,02%	160,8
AGENT	299	1,33%	0,69%	0,36%	72	10,78%	289,3
BASED	294	1,31%	0,68%	0,35%	179	26,80%	168,1
SERVER	291	1,30%	0,67%	0,35%	90	13,47%	253,3
RESPONSE	252	1,12%	0,58%	0,30%	107	16,02%	200,4
INPUT	226	1,01%	0,52%	0,27%	102	15,27%	184,5
INVENTION	215	0,96%	0,50%	0,26%	149	22,31%	140,1
BRAIN	211	0,94%	0,49%	0,25%	57	8,53%	225,5
PROVIDED	206	0,92%	0,48%	0,25%	166	24,85%	124,6
INCLUDES	196	0,87%	0,45%	0,24%	147	22,01%	128,9
IMAGE	186	0,83%	0,43%	0,22%	64	9,58%	189,5
EP	178	0,79%	0,41%	0,21%	178	26,65%	102,2
SERVICE	178	0,79%	0,41%	0,21%	71	10,63%	173,3
SOLUTION	178	0,79%	0,41%	0,21%	171	25,60%	105,3
COMMUNICATION	176	0,78%	0,41%	0,21%	76	11,38%	166,1
MESSAGE	169	0,75%	0,39%	0,20%	56	8,38%	181,9
CONVERSATION	167	0,74%	0,39%	0,20%	53	7,93%	183,8
DISPLAY	167	0,74%	0,39%	0,20%	69	10,33%	164,6
CHATBOT	166	0,74%	0,38%	0,20%	62	9,28%	171,4
LANGUAGE	164	0,73%	0,38%	0,20%	51	7,63%	183,2
CONTENT	163	0,73%	0,38%	0,20%	63	9,43%	167,1
JP	163	0,73%	0,38%	0,20%	163	24,40%	99,9

Since this preliminary analysis only identifies the most frequent words appearing in the title or in the abstract of the patents (user, information, system, data and service as the first five), a further analysis of the topics (Table 2) and phrases (Table 3) allows the identification of the group of words with a common sense

Table 2. Identification of the main topics.

NO	NAME	KEYWORDS	EIGENVALUE	% VAR	FREQ	CASES	% CASES
1	CONVERSATION; QUESTION/ANSWER	CONVERSATIONAL; ANSWER; QUESTION; STORES; CONVERSATION; AGENT; SERVICE; KR; DATABASE; VISITOR; SERVER; PREFERENCE; USER; CONTENTS; ANALYZING	15,35	2,23	772	385	57,63%
2	JPO; COPYRIGHT	JPO; COPYRIGHT; INPIT; SOLVED; JP; SOLUTION; INFORMATION	6,61	1,64	216	200	29,94%
3	EP	EP; DISORDERS; DISEASES; COMPOUNDS; METHODS; COMPOSITIONS; TREATING; TREATMENT; USEFUL; RELATES; INVENTION; DISEASE	5,61	1,69	904	447	66,92%
4	PROCESSOR; INPUT	PROCESSOR; INPUT; OUTPUT; RECEIVE; CONFIGURED; STORED; INTERFACE; DEVICE; MEMORY; RESPONSE; INSTRUCTION; RECEIVED; AUDIO	5,47	1,21	299	181	27,10%
5	PHRASE; DOMAIN SCORE	PHRASE; DOMAIN; SENTENCE; SCORE; MODULE; TERM; INTENT; VECTOR; CHARACTER; ENTITY; CALCULATION; KR; WORD	4,7	1,67	449	257	38,47%
6	SUBSCRIBER; IDENTIFIER	SUBSCRIBER; IDENTIFIER; SUBSET; MEMORY; COMPUTING; TRANSMITTING; DETERMINATION; SELECTING; MESSAGING; GENERATING; DETERMINING; RECORD	3,46	1,21	810	360	53,89%
7	SELECTED DRAWING; FIGURE	DRAWING; FIGURE; SELECTED; KEYWORD; KEYWORDS; BASIS; SOLVED; JP; SOLUTION	3,25	1,27	215	136	20,36%
8	STIMULATION; RECORD	STIMULATION; RECORD; UPPER; RANGE; PARAMETERS; PATIENT; DISCLOSED; CONFIGURED; CONTROL	3,2	1,09	286	181	27,10%
9	CONFERENCE; VIDEO	CONFERENCE; VIDEO; CAMERA; IMAGE; IMAGES; FACE; SIDE; REMOTE; TERMINAL; COMMUNICATION	3,07	1,12	85	67	10,03%
10	CLOUD; CALLBACK	CLOUD; CALLBACK; REQUEST; PROVIDING; RECEIVE; ELEMENTS; DETERMINED; FILE; MEDIA; SERVER; MANAGEMENT; SERVICE	2,99	1,09	237	160	23,95%

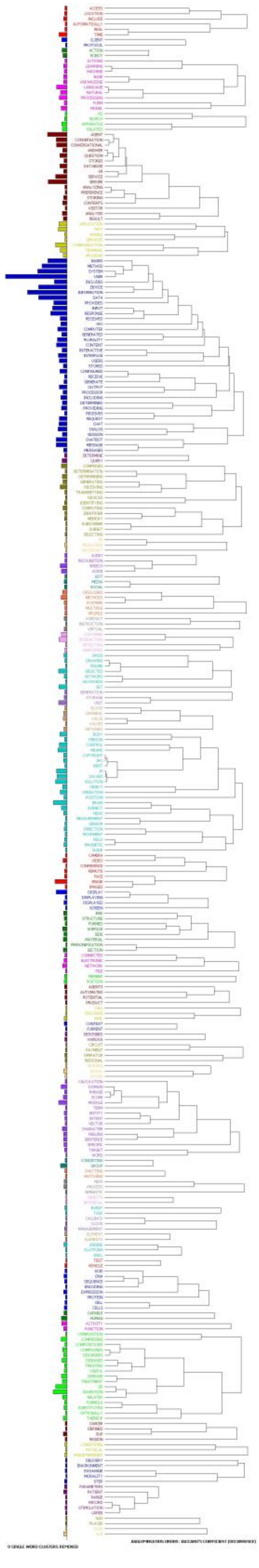
Table 3. Identification of the main phrases.

	FREQUENCY	NO. CASES	% CASES	LENGTH	TF • IDF
CONVERSATIONAL AGENT	127	19	2,84%	2	196,3
NATURAL LANGUAGE	89	37	5,54%	2	111,8
DIALOG SYSTEM	70	10	1,50%	2	127,7
AGENT SERVICE	50	17	2,54%	2	79,7
CONVERSATIONAL AGENT SERVICE	47	16	2,40%	3	76,2
COMPUTING DEVICE	45	19	2,84%	2	69,6
INVENTION RELATES	45	43	6,44%	2	53,6
SERVICE SERVER	45	18	2,69%	2	70,6
USER INTERFACE	43	23	3,44%	2	62,9
AGENT SERVICE SERVER	38	15	2,25%	3	62,7

The identification of main topics and phrases confirms the emphasis on conversation (including conversational, answer, question, stores, and agents in Table 2), and conversational agent and natural language (Table 3). As a consequence, the patents on chatbot are mainly related to systems/methods/devices for conversational agents able to simulate the natural language, which might lead to better interactions between consumers and retailer (online digital assistant). This finding is in line with recent calls soliciting the necessity of improved conversational abilities by chatbots that allow both a better identification of consumers' reactions from their natural language, and a more accurate assessment of the quality of the relationship with the customer (Chakrabarti and Luger, 2015).

A further identification of clusters (word categories), performed through the dendrogram details how the words are connected to each other towards the formation of homogeneous clusters of chatbot features (based on the Jaccard's similarity coefficient) (Figure 2).

Figure 2. The identification of clusters (word categories) through the dendrogram (based on the Jaccard's similarity coefficient).



This analysis corroborates the findings identified in the previous analyses, and adds new evidence by showing the mutual relationships among the patented features of chatbots. Thus, results from the cluster analysis reinforce the pivotal role played by the ability of chatbots to automatically understand and process users' (consumers') language and information. For instance, in Cluster 1 the word "Automatically" is tightly linked to "Real time", as evidenced by the value of the Jaccardi's similarity coefficient, and grouped together with "Access" and "Location", thereby suggesting a potential avenue for future research based on the ability of chatbots to detect in real-time the location of the user and adapt the content of the information accordingly. Similarly, Cluster 10 emphasizes the relationship between sets of keywords related with the data management and analysis such as "Determination/Determining", "Generating", "Receiving", "Transmitting", "Identifying", and "Computing". Also, Cluster 4 (the 4th from the top) addresses the role of machine learning techniques in the processing of individuals' natural language, as suggested by the link identified between "Machine Learning" and "Natural Language", which appear together with words such as "Actions", "Knowledge", "Base", and "Processing" among others. The ability to interactively obtain user-based information to determine the most appropriate communication strategy is further highlighted by Cluster 8 (the 8th from the top), which is the densest cluster and includes the connection between users, method, information, data, chat and dialog. Likewise, Cluster 6 focuses on conversational agents and their analytical skills in deriving and storing users' preferences in databases, consistently with Cluster 16 that stresses the relevance of "Customer Interaction" associated with "Detecting" and "Identified". Findings suggest also different input data for chatbots that might set the direction for research and practice in the near future, such as "Instant Messaging" (Cluster 11), "Audio Recognition" (Cluster 12), or "Social Media" (Cluster 13).

5. Discussion and Conclusion

The extant literature has extensively studied the antecedents and consequences of chatbot adoption (Sivaramakrishnan, Wan and Tang, 2007), hypothesizing how conversational agents in the (near) future would be (Beldad, Hegner and Hoppen, 2016; Saunila, Ukko, and Rantala, in press; Nowak and Rauh, 2008; Mou and Xu, 2017). Literature also emphasized the increasing importance of chatbots as a new effective form of digital assistants to support consumer assistance (Verhagen, et al., 2014; Aldiri, Hobbs, and Qahwaji, 2008; Keeling, McGoldrick, and Beatty, 2010; Potdar, et al., 2018). However, to the best of our knowledge, the present research is the first study adopting patent analysis as elective methodology in order to incorporate the innovative stimuli coming from the investments in research and development, which might result into re-shaped digital agents, which in turn would impact retailing and online retail domain.

Our study contributes to extant literature on chatbots by (i) indicating the actual areas of developments (as the areas where the invention effort in greater in terms of number of patents), which might result into the availability of new chatbots to be introduced, and (ii) providing a comprehensive understanding of the actual progresses in chatbots. Since findings refers to the patented inventions related to chatbot, our results also indicate the type of innovations that would further affect retailing, when (and if) those innovation will be put into practice. In particular, the present research highlights the main domains of research and development (Figure 1) as "Computer technology" (for instance, including the patents related to the new algorithms to improve the system responsiveness, the natural language processing, and so on), "digital communication" (for instance, including new interactive dialog interfaces), "pharmaceutical" and "IT methods for management" (for instance including new techniques for understanding why a consumer interrupts the transactions as the financial ones). This latter group shows also the extent to which the progresses in technology are attempting to reply to the challenge posited in terms of chatbots responsiveness (Hill, Ford and Farreras, 2015; Shah et al., 2016), as a critical issue for marketing and retail application. With the only relevant exception of “pharmaceutical”, results further identify that a huge amount of innovation in the domain of chatbot patents seems to tap directly into the area of online retailing, or marketing and retailing in general. Thus, our research investigates the recent technology push towards the adoption of new conversational agents based on natural language, while we would expect that chatbots development will be guided by general studies in this sense.

Results from the cluster analysis on the patents’ keywords highlight also the critical areas for innovating (as emerged in our clusters). When focusing specifically on cluster 11 (“Instant Messaging), cluster 12 (audio recognition), cluster 13 (social media) and cluster 16 (related to “Customer Interaction” and “Detecting” and “Identified”, the huge research effort in this direction clearly emerges, as evident in the increasing interest in social media as Facebook Messenger and Twitterbots (Instant messaging), and audio recognition (i.e., Alexa, Siri, etc.). These areas of development are devoted to improve chatbots’ ability to automatically draw inferences on users starting from multiple data sources, and to use this information adaptively to provide users with more customized solutions. Thus, they synthetize the current trends in the industry and the innovations in the field of digital agents that are more likely to take place.

From a practical point of view, on the one hand, retailers will continuously have more sophisticated systems to exploit for providing assistance to consumers, by soliciting their constant monitoring of the progresses in this sense; on the other hand they will need more capabilities to understand how to detect, select and implement the best technology for the specific retail purposes. In particular, our study would support retailers in the identification of the current technology supply, by providing knowledge for their subsequent innovation investment decisions in this sense. To this end, retailers might adopt two main strategies: (i) adopting off-the-shelf products through technology providers (as IBM Azure and Microsoft Watson or Google Cloud among the others), or ii) building from the scratch their own solutions in their R&D departments by using, for instance, Python and Wolfram Mathematica. In the former case, retailers would have the advantage to invest their resources to implement and adapt existing technological solutions into their business; while in the latter case, they would use their resources to internally develop a new solution that would serve exclusively their business.

Nevertheless, our study shows a still limited theoretical advancement towards the topics of conversational agents, dialog systems and consumer digital interfaces from a marketing and retail (both online and offline) management perspective. Indeed, our research is strongly focused on the understanding of the supply of digital assistance, rather than investigating how consumers are likely to accept such a new wave of technological innovation. Thus, more research is needed to understand whether and to what extent the innovative features of conversational agents highlighted by the present research are going to significantly affect customer interactions and usage. These interactions can be further investigated in terms of how customers will approach the agents and conduct the conversation, and how the agents will be integrated within the webpage (and mobile sites) layout. Accordingly, future studies might benefit from the results of this analysis by identifying innovative features of digital agents, and providing new empirical and theoretical knowledge that will help understanding whether these features can be profitably incorporated on retail settings, embracing online, mobile and omnichannel perspectives.

References

Abraham, B.J., & Moitra, S.D. (2001). Innovation assessment through patent analysis. *Technovation*, *21*(4), 245-252.

Admoni, H., & Scassellati, B. (2017). Social eye gaze in human-robot interaction: a review. *Journal of Human-Robot Interaction*, *6*(1), 25-63.

Aldiri, K., Hobbs, D., & Qahwaji, R. (2008). The human face of e-business: Engendering consumer initial trust through the use of images of sales personnel on e-commerce web sites. *International Journal of E-Business Research, 4*(4), 58-78.

Alfano, M., Pagnotta, L., & Pantano, M.F. (2011). A review of patented works on the mechanical characterization of material at micro- and nano-scale. *Recent Patents on Nanotechnology*, *5*(1), 37-45.

Almansor, E. H., & Hussain, F. K. (2019, July). Survey on Intelligent Chatbots: State-of-the-Art and Future Research Directions. In *Conference on Complex, Intelligent, and Software Intensive Systems* (pp. 534-543). Springer, Cham.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., ... & Yang, H. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data. *Customer Needs and Solutions*, *5*(1-2), 28-37.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior, 85*, 183-189.

Ariely, D., Lynch Jr, J. G., & Aparicio IV, M. (2004). Learning by collaborative and individual-based recommendation agents. *Journal of Consumer Psychology*, *14*(1-2), 81-95.

Arsovski, S., Wong, S., & Cheok, A. D. (2018). Open-domain neural conversational agents: The step towards artificial general intelligence. *International Journal of Advanced Computer Science and Applications*, *9*(6), 402-408.

Arsovski, S., Osipyan, H., Oladele, M. I., & Cheok, A. D. (2019). Automatic knowledge extraction of any Chatbot from conversation. *Expert Systems with Applications*, *137*, 343-348.

Beck, A., Cañamero, L., Hiolle, A., Damiano, L., Cosi, P., Tesser, F., & Sommavilla, G. (2013). Interpretation of emotional body language displayed by a humanoid robot: A case study with children. *International Journal of Social Robotics*, *5*(3), 325-334.

Belavina, E., Girotra, K., & Kabra, A. (2017). Online grocery retail: revenue models and environmental impact. *Management Science, 63*(6), 1781-1799.

Beldad, A., Hegner, S., & Hoppen, J. (2016). The effect of virtual sales agent (VSA) gender–product gender congruence on product advice credibility, trust in VSA and online vendor, and purchase intention. *Computers in Human Behavior, 60*, 62-72.

Bell, D.R., Gallino, S., & Moreno, A. (2017). Offline showrooms in omnichannel retail: demand and operational benefits. *Management Science, 64*(4), 1629-1651.

Bitner, M.J., Brown, S.W., & Meuter, M.L. (2000). Technology infusion in service encounters. *Journal of the Academy of Marketing Science, 28*(1), 138-149.

Block, J., Miller, D., Jaskiwicz, P., & Spiegel, F. (2013). Economic and technological importance of innovation in large family and founder firms: an analysis of patent data. *Family Business Review, 26*(2), 180–199.

Bodapati, A.V. (2008). Recommendation systems with purchase data. *Journal of Marketing Research, 45*(1), 77-93.

Bozer, Y.A., & Aldarondo, F.J. (2018). A simulation-based comparison of two goods-to-person order picking systems in an online retail setting. *International Journal of Production Research, 56*(11), 3838-3858.

Burke, R.R. (2002). Technology and the customer interface: what consumers want in the physical and virtual store. *Journal of the Academy of Marketing Science, 30*(4), 411-432.

Castro-González, Á., Admoni, H., & Scassellati, B. (2016). Effects of form and motion on judgments of social robots′ animacy, likability, trustworthiness and unpleasantness. *International Journal of Human-Computer Studies*, *90*, 27-38.

Chakraborty, R., Lee, J., Bagchi-Sen, S., Upadhyaya, S., & Raghav Rao, H. (2016). Online shopping intention in the context of data breach in online retail stores: An examination of older and younger adults. *Decision Support Systems, 83*(1), 47-56.

Chakrabarti, C., & Luger, G. F. (2015). Artificial conversations for customer service chatter bots: Architecture, algorithms, and evaluation metrics. *Expert Systems with Applications, 42*(20), 6878-6897.

Chang, S.-B. (2012). Using patent analysis to establish technological position: Two different strategic approaches. *Technological Forecasting and Social Change, 79*(1), 3-15.

Chang, H.H., Fu, C.S.F., Fang, P.W., & Cheng, Y.-C. (2016). The effect of relationship maintenance and relationship investment on self-service technology relationship performance. *Information Technology & People, 29*(3), 496-526.

Chatterjee, A., Gupta, U., Chinnakotla, M. K., Srikanth, R., Galley, M., & Agrawal, P. (2019). Understanding emotions in text using deep learning and big data. *Computers in Human Behavior*, *93*, 309-317.

Choi, Y.K., Miracle, G.E., & Biocca, F. (2001). The effects of anthropomorphic agents on advertising effectiveness and the mediating role of presence. *Journal of Interactive Advertising, 2*(1), 19-32.

Culley, K.E., & Madhavan, P. (2013). A note of caution regarding anthropomorphism in HCI agents. *Computers in Human Behavior, 29*(3), 577-579.

Daim, T.U., Rueda, G., Martin, H., & Gersdri, P. (2006). Forecasting emerging technologies: use of bibliometrics and patent analysis. *Technological Forecasting & Social Change*, *73*, 981-1012.

Davelembayeva, D., Papagiannidis, S., & Alamanos, E. (in print). Mapping the economics, social and technological attributes of the sharing economy. *Information Technology and People*.

Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics, 1*(2), 73-80.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24-42.

Davenport, T. H., & Kirby, J. (2016). Just how smart are smart machines?. *MIT Sloan Management Review*, *57*(3), 21.

De Bruyn, A., Liechty, J.C., Huizingh, E.K., & Lilien, G.L. (2008). Offering online recommendations with minimum customer input through conjoint-based decision aids. *Marketing Science, 27*(3), 443-460.

De Keyser, A., Köcher, S., Alkire, L., Verbeeck, C., & Kandampully, J. (2019). Frontline Service Technology infusion: conceptual archetypes and future research directions. *Journal of Service Management*, *30*(1), 156-183.

Demmers, J., van Dolen, W.M., & Weltevreden, J.W.J. (2018). Handling Consumer Messages on Social Networking Sites: Customer Service or Privacy Infringement?. *International Journal of Electronic Commerce, 22*(1), 8-35.

Felfernig, A., Friedrich, G., Jannach, D., & Zanker, M. (2006). An integrated environment for the development of knowledge-based recommender applications. *International Journal of Electronic Commerce, 11*(2), 11-34.

Flanagin, A. J., Metzger, M. J., Pure, R., Markov, A., & Hartsell, E. (2014). Mitigating risk in ecommerce transactions: perceptions of information credibility and the role of user-generated ratings in product quality and purchase intention. *Electronic Commerce Research, 14*(1), 1-23.

Fryer, L. K., Nakao, K., & Thompson, A. (2019). Chatbot learning partners: Connecting learning experiences, interest and competence. *Computers in Human Behavior, 93*, 279-289.

Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature*, *521*(7553), 452.

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior, 97*, 304-316.

Grand View Research (2017). *Chatbot Market Size To Reach $1.25 Billion By 2025*. CAGR: 24.3%. Retrieved from: https://www.grandviewresearch.com/press-release/global-chatbot-market

Gretzel, U., & Fesenmaier, D. R. (2006). Persuasion in recommender systems. *International Journal of Electronic Commerce, 11*(2), 81-100.

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The future of retailing. *Journal of Retailing, 93*(1), 1-6.

Griol, D., & Callejas, Z. (2016). Mobile conversational agents for context-aware care applications. *Cognitive Computation, 8*(2), 336-356.

Griol, D., Carbó, J., & Molina, J. M. (2013). An automatic dialog simulation technique to develop and evaluate interactive conversational agents. *Applied Artificial Intelligence, 27*(9), 759-780.

Hill, J., Ford, W.R., & Farreras, I.G. (2015). Real conversations with artificial intelligence: a comparison between human-human online conversations and human-chatbot conversations. *Computers in Human Behavior, 49*, 245-250.

Holzwarth, M., Janiszewski, C., & Neumann, M. M. (2006). The influence of avatars on online consumer shopping behavior. *Journal of Marketing, 70*(4), 19-36.

Hostler, R. E., Yoon, V. Y., Guo, Z., Guimaraes, T., & Forgionne, G. (2011). Assessing the impact of recommender agents on on-line consumer unplanned purchase behavior. *Information & Management, 48*(8), 336-343.

Huang, M.-U., & Rust, R.T. (2017). Technology-driven service strategy. *Journal of The Academy of Marketing Science, 45*, 906-924.

Huang, M.-U., & Rust, R.T. (2018). Artificial intelligence in Service. *Journal of Service Research, 21*(2), 155-172.

Humphreys, A., & Wang, R. J.-H. (2018). Automated text analysis for consumer research. *Journal of Consumer Research, 44*, 1274-1306.

Jacoby, J. (1977). Information load and decision quality: Some contested issues. *Journal of Marketing Research*, 569-573.

Keeling, K., McGoldrick, P., & Beatty, S. (2010). Avatars as salespeople: Communication style, trust, and intentions. *Journal of Business Research, 63*(8), 793-800.

Kim, G., & Bae, J. (2017). A novel approach to forecast promising technology through patent analysis. *Technological Forecasting and Social Change*, *117*, 228-237.

Lai, H. (2000). An Object-Oriented Architecture for Intelligent Virtual Receptionists. *International Journal of Electronic Commerce*, *4*(3), 69-86.

Lapple, D., Renwick, A., & Thorne, F. (2015). Measuring and understanding the drivers of agricultural innovation: evidence from Ireland. *Food Policy, 51*, 1–8.

Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., Wünderlich, N.V., & De Keyser, A. (2017). Service Encounter 2.0: An investigation into the roles of technology, employees and customers. *Journal of Business Research, 79*, 238-246.

Lee, S., & Choi, J. (2017). Enhancing user experience with conversational agent for movie recommendation: Effects of self-disclosure and reciprocity. *International Journal of Human-Computer Studies*, *103*, 95-105.

Lee, C., Jeon, J., & Park, Y. (2011). Monitoring trends of technological changes based on the dynamic patent lattice: a modified formal concepts analysis approach. *Technological Forecasting & Social Change*, *78*(4), 690-702.

Lee, S., Yoon, B., Lee, C., & Park, J. (2009). Business planning based on technological capabilities: patent analysis for technology-driven road mapping. *Technological Forecasting and Social Change, 76*(6), 769-786.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, *38*(6), 937-947.

Mathur, M. B., & Reichling, D. B. (2016). Navigating a social world with robot partners: A quantitative cartography of the Uncanny Valley. *Cognition*, *146*, 22-32.

Mcginty, L., & Smyth, B. (2006). Adaptive selection: An analysis of critiquing and preference-based feedback in conversational recommender systems. *International Journal of Electronic Commerce*, *11*(2), 35-57.

Mimoun, M. S. B., Poncin, I., & Garnier, M. (2012). Case study—Embodied virtual agents: An analysis on reasons for failure. *Journal of Retailing and Consumer Services*, *19*(6), 605-612.

Mimoun, M.S.B., Poncin, I., & Garnier, M. (2017). Animated conversational agents and e-consumer productivity: The roles of agents and individual characteristic. *Information & Management*, *54*(5), 545-559.

Mitra, K., Reiss, M.C., & Capella, L.M. (1999). An examination of perceived risk, information search and behavioral intentions in search, experience and credence services. *Journal of Services Marketing*, *13*(3), 208-228.

Mou, Y., & Xu, K. (2017). The media inequality: comparing the initial human-human and human-AI social interactions. *Computers in Human Behavior*, *72*, 432-440.

Murray, K.B., & Häubl, G. (2009). Personalization without interrogation: Towards more effective interactions between consumers and feature-based recommendation agents. *Journal of Interactive Marketing*, *23*(2), 138-146.

Nelson, A., Earle, A., Howard-Grenville, J., Haack, J., & Young, D. (2014). Do innovation measures actually measure innovation? Obliteration, symbolic adoption, and other finicky challenges in tracking innovation diffusion. *Research Policy, 43*(6), 927-940.

Nowak, K.L., & Rauh, C. (2008). Choose your "buddy icon" carefully: The influence of avatar androgyny, anthropomorphism and credibility in online interactions. *Computers in Human Behavior, 24*(4), 1473-1493.

Nuruzzaman, M., & Hussain, O.K. (2018, October). A Survey on Chatbot Implementation in Customer Service Industry through Deep Neural Networks. In *2018 IEEE 15th International Conference on e-Business Engineering (ICEBE)* (pp. 54-61). IEEE.

Pantano, E., Priporas, C.-V., Sorace, S., & Iazzolino, G. (2017). Does the innovation-orientation lead to retail industry growth? Empirical evidence from patent analysis. *Journal of Retailing and Consumer Services, 34,* 88-94.

Pantano, E., Priporas, C.-V., & Stylos, N. (2018). Knowledge push curve (KPC) in retailing: evidence from patented innovations analysis affecting retailers' competitiveness. *Journal of Retailing and Consumer Services, 44*, 150-160.

Pantano, E., & Vannucci V. (2019). Who is innovating? An evaluation of the extent to which retailers are meeting the technology challenge. *Journal of Retailing and Consumer Services, 49,* 297-304.

Papagiannidis, S., Pantano, E., See-To, E., Dennis, C., & Bourlakis, M. (2017). To immerse or not? Experimenting with two virtual retail environments. *Information Technology & People, 34*(1), 163-188.

Park, C.H., & Kim, Y.G. (2003). Identifying key factors affecting consumer purchase behavior in an online shopping context. *International Journal of Retail & Distribution Management, 31*(1), 16-29.

Park, Y., Yoon, B., & Lee, S. (2005). The idiosyncrasy and dynamism of technological innovation across industries: patent citation analysis. *Technology in Society, 27*(4), 471-485.

Potdar, V., Joshi, S., Harish, R., Baskerville, R., & Wongthongtham, P. (2018). A process model for identifying online customer engagement patterns on Facebook brand pages. *Information Technology & People, 31*(2), 595-614.

Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems, 25*(4), 145-182.

Rust, R. T., & Huang, M. H. (2014). The service revolution and the transformation of marketing science. *Marketing Science, 33*(2), 206–221.

Satzger, B., Endres, M., & Kießling, W. (2006). A preference-based recommender system. *Proceedings of the International Conference on Electronic Commerce and Web Technologies*, Springer-Verlag, Berlin, pp. 31-40.

Saunila, M., Ukko, J., & Rantala, T. (in print). Value co-creation through digital service capabilities: the role of human factors. *Information Technology & People*.

Seifoddini, H., & Djassemi, M. (1991). The production data-based similarity coefficient versus Jaccard's similarity coefficient. *Computers & Industrial Engineering, 21*(1/4), 263-266.

Shah, H., Warwick, K., Vallverdú, J., & Wu, D. (2016). Can machines talk? Comparison of Eliza with modern dialogue systems. *Computers in Human Behavior, 58*, 278-295.

Shankar, V. (2018). How artificial intelligence (AI) is reshaping retailing. *Journal of Retailing, 94*(4), 6–11.

Silver, C. (2014). Qda Miner (With Wordstat and Simstat). *Journal of Mixed Methods Research*, *9*(4), 386-387.

Sivaramakrishnan, S., Wan, F., & Tang, Z. (2007). Giving an “e-human touch” to e-tailing: The moderating roles of static information quantity and consumption motive in the effectiveness of an anthropomorphic information agent. *Journal of Interactive Marketing*, *21*(1), 60-75.

Swaminathan, V. (2003). The impact of recommendation agents on consumer evaluation and choice: the moderating role of category risk, product complexity, and consumer knowledge. *Journal of Consumer Psychology, 13*(1-2), 93-101.

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management*, *69*, 135-146.

Tay, B.T.C., Low, S.C., Ko, K.H., & Park, T. (2016). Types of humor that robots can play. *Computers in Human Behavior*, *60*, 19-28.

Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness: When does the message get through? *Computers in Human Behavior, 98*, 150-157.

Verhagen, T., Van Nes, J., Feldberg, F., & Van Dolen, W. (2014). Virtual customer service agents: Using social presence and personalization to shape online service encounters. *Journal of Computer-Mediated Communication*, *19*(3), 529-545.

Willems, K., Smolders, A., Brengman, M., Luyten, K., & Schoning, J. (2017). The path-to-purchase is paved with digital opportunities: an inventory of shopper-oriented retail technologies. *Technological Forecasting and Social Change, 124*, 228-242.

Wilson, J.R., Lee, N.Y., Saechao, A., Hershenson, S., Scheutz, M., & Tickle-Degnen, L. (2017), "Hand gestures and verbal acknowledgments improve human-robot rapport", in Kheddar, A., Yoshida, E., Ge, S.S., Suzuki, K., Cabibihan, J.-J., Eyssel, F. and He, H. (Eds), *Social Robotics*, Springer International Publishing, Cham, pp. 334-344.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, *29*(5), 907-931.

Yoo, W-S., Lee, Y., & Park, J.K. (2010). The role of interactivity in e-tailing: creating value and increasing satisfaction. *Journal of Retailing and Consumer Services, 17*(2), 89–96.

Yoon, V.Y., Hostler, R.E., Guo, Z., & Guimaraes, T. (2013). Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. *Decision Support Systems, 55*(4), 883-893.

Zanker, M., Bricman, M., & Jessenitschnig, M. (2011). Cost-effective development of virtual sales assistants. In Damiani, E., Jeong, J., Howlett, R.J. and Jain, L.C. (Eds.), *New directions in intelligent multimedia systems and services*, Springer-Verlag, Berlin-Heidelberg, pp. 1-11.

Tables

Table 1. Identification of the occurrences.

Table 2. Identification of the main topics.

Pantano E., Pizzi G. *(in press).* Forecasting artificial intelligence on online customer assistance: evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services*.