Computers in Human Behavior 51 (2015) 1284–1294

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Mining social network users opinions' to aid buyers' shopping decisions

Ernesto D'Avanzo [a,b,*], Giovanni Pilato [b]

[a] Dept. of Political, Social and Communication Sciences, University of Salerno, Via Giovanni XXIII, 84084 Fisciano (Salerno), Italy
[b] ICAR – CNR, Italian National Research Council, Viale delle Scienze, 90128 Palermo, Italy

ARTICLE INFO

Article history:
Available online 18 December 2014

Keywords:
Social sentiment analysis
Buyers' behaviors
Heuristics
Bayes' learning
Collaborative decision support systems

ABSTRACT

More and more online buyers turn to online reviews, while shopping, to get support in their choices. For instance, D'Avanzo and Kuflik (2013) show that more than 80% of buyers, while shopping online, expect *user's* or *professional reviews* services, implemented on the seller's website, that can be consulted before their purchase could take place. However, the diffusion of information, that buyers deal with during their shopping experience, makes room to the information and cognitive overload an out-and-out curse. All that is causing sellers adding Web decision support services to help buyers with their decision-making processes and there is a growing number of studies focusing on the enhancing of buyers online shopping decisions with the aim to improve their subjective attitudes towards shopping decisions. More and more sellers add on their side web decision support services that implement decision strategies employed by individuals to arrive at decisions and purchases. This paper introduces a cognitively based procedure (Gopnik et al., 2004) that mines users opinions from specific kinds of market, visually summarizing them in order to alleviate buyers overload and speeding up her/his shopping activity. The proposed approach emulates Vygotsky's theory of *zone of proximal development* that is well-known in the collaborative learning community (Chiu, 2000).

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

The increase of user generated content in the form of reviews is straight proportional to the rapid expansion of online shopping that, according to a report by Forrester research,[1] accounts for 13% of total retail sales in 2010 (Gudigantala, Song, & Jones, 2008). The easing both for sellers to transmit large amount of information at a low cost and for buyers to reduce the effort of getting at the information they are interested in, should have made the buyers shopping activity easier. Furthermore, this information diffusion about products imagined buyers satisfied during purchase decisions and, in general, shopping experiences, because in a brick-and-mortar of the traditional marketplace, more information was turned into better buyers decisions (Russo, 1974). However, the diffusion of information, that buyers deal with during their shopping experience, makes room to the curse of information overload (Cheng, Sun, & Zeng, 2010), a problem difficult to deal with (Karr-Wisniewski & Lu, 2010; Sicilia & Ruiz, 2010), especially if we consider the chief role played by buyers cognitive states because of their limited information processing capabilities (Iyengar, Wells, & Schwartz, 2006; Simon, 1956; Tversky & Kahneman, 1990).

Globalization and internationalization has pushed companies to improve customer satisfaction and get better results (Gonzlez-Gonzlez, Serradell-Lpez, & Castillo-Merino, 2012). In last years, community put a lot of effort for developing Web/shopping decision support systems that may help buyers finding the most relevant information (Resnick & Varian, 1997; Turban, Aronson, Liang, & Sharda, 2007; Xiao & Benbasat, 2007), spawning a lot of interdisciplinary interest (Alba et al., 1997; HŁubl & Murray, 2003; HŁubl & Trifts, 2000; Kowatsch & Maass, 2010; Lee & Lee, 2009; Murray & HŁubl, 2009; Qiu & Benbasat, 2010; Wang & Doong, 2010) and Knowledge Society is playing a crucial role nowadays (Lytras & de Pablos, 2011). For instance, cognitive scientists (Newell & Simon, 1976; Oulasvirta, Hukkinen, & Schwartz, 2009) debate on the role that individual factors, together with external information, play in the decision making process and there is a growing number of studies focusing on the enhancing of buyers online shopping decision with the aim to improve their subjective attitudes towards shopping decisions (Gupta & Harris, 2010; Kukar-Kinney & Close, 2010; Lee & Lee, 2004, 2009; Toncovich, Turn, Escobar, & Moreno-Jimnez, 2011). All that is causing sellers adding Web decision support services to help buyers with their decision-making processes (Lin, Hong, Chen, & Dong, 2010; Mohanty, Ravi, & Patra, 2010; Papatla & Liu, 2009). These services can be implemented by using decision strategies, i.e., rules, either referred to as heuristics (Marewski, Schooler, & Gigerenzer, 2010;

* Corresponding author at: Dept. of Political, Social and Communication Sciences, University of Salerno, Via Giovanni XXIII, 84084 Fisciano (Salerno), Italy.

[1] http://www.forrester.com.

http://dx.doi.org/10.1016/j.chb.2014.11.081
0747-5632/© 2014 Elsevier Ltd. All rights reserved.

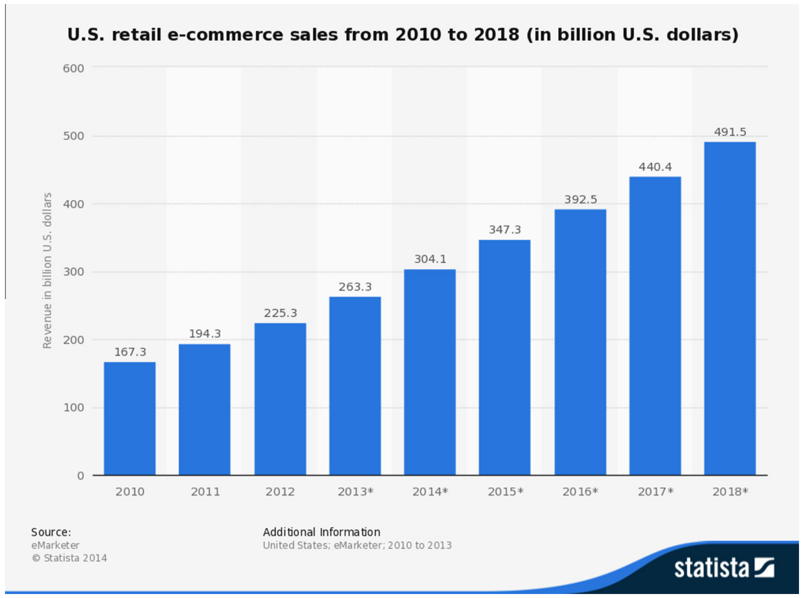

Fig. 1. Figure report on the past E-commerce sales in U.S. Projections up to 2018 show a continuously and increasing marketplace.

Pearl, 1984; Polya, 1945), or rules of thumb (Gigerenzer, 2007; Waksberg, Smith, & Burd, 2009), employed by individuals to arrive at decisions and purchases (Hogarth, 1987; Jedetski, Adelman, & Yeo, 2002).

Authors of D'Avanzo and Kuflik (2013), investigating exactly the role that these strategies play both on the seller's and the buyer's side, found that among these heuristics, implemented on the seller's site as web services, *users' reviews* and *professional reviews* are expected to be implemented as web services by more than 80% of buyers. This result has also been found to be correlated with the *frequency heuristics* according to, the mere number of positive or negative attribute of a product (i.e., *product polarity*), plays a key role in buyer's decision making. As properly supported by Vinodhini and Chandrasekaran (2014), a need to organize the E-commerce reviews arises to help users and organizations in making an informed decision about the products.

This paper introduces a cognitive based methodology (Gopnik et al., 2004) to identify the *user/product polarity*. The approach, described in Section 3 employs a well known learning algorithm and an accomplished feature selection method, respectively a *Bayesian learner* and a *TF-IDF* based selector.

The approach has been tested on two kinds of market reviews gathered on the Facebook page, namely *smartphones* (i.e., Nokia) and *fashion* (i.e., Zalando and Privalia). The approach, tested using standard evaluation metrics such as those employed by related applications reported in Section 2, shows stimulating results. As ongoing work we are testing how the buyer's benefits from the use of a visual summary of products' reviews in her/his shopping activity. In other words the systems will be tested as a decision support system able to increase the buyer's level of satisfaction and a corresponding decreasing of his overload while shopping online. On the whole, buyers benefit of the social roots of the reviews mined, emulating a well-known approach used in collaborative learning, that is Vygotsky's theory of *zone of proximal development* (ZPD) (Chiu, 2000). As is known ZPD is the difference between what a learner can do without help and what he or she can do with help Lee and Smagorinsky (2000). In our case the ZPD is the difference between what a buyer can do without help and what he or she can do with help of the social opinion mining tool tested in this work.

2. Motivation: sellers' opportunities and buyers' behaviors

Even though *online shopping* is mostly considered in the same ways as *E-commerce*, actually *online shopping* is a sub-category of E-commerce as it predominantly refers to business-to-consumer (B2C) transactions such as online retail or online auctions (Drigas & Leliopoulos, 2013). *Online shopping* also refers to online purchases from bricks-and-mortar retailers or from online retailing corporations such as Amazon.com or Alibaba. According to STATISTA,[2] the *online shopping* marketplace has considerably grown over the past decade. For instance, in 2012 U.S. E-commerce sales amounted to 289 billion U.S. dollars, up from 256 billion U.S. dollars in 2011, with the largest share of online revenue produced by retail shopping websites that earned 210.3 billion U.S. dollars in 2013. According to a current STATISTA E-commerce forecast, online retail revenue in the U.S., as shown in Fig. 1, are expected to increase up to 500 billion U.S. dollars in 2018.

In terms of development, facts and figures do not change if we turn our attention to online marketplaces outside U.S. For instance, in Germany retail revenues were about 43 billion U.S. dollar in 2013 and are projected to grow to 58.38 billion U.S. dollars in 2017 in spite of the cutting economic crisis prevailing in Europe. Developing markets as well show final balance revenues at the moment and promise growing markets for the future. India's E-commerce sales in 2013 amounted to 3.59 billion U.S. dollars and are expected to grow up to 14 billion U.S. dollars in 2017. China's market then represents a phenomenon on its own if we consider that in 2013 retail E-commerce sales amounted to 141.64 billion U.S. dollars and are projected to grow to 665.07 billion U.S. dollars in 2017. Fig. 2 show the monthly reach of retail websites across BRIC countries as of March 2013, when retail websites reached around 60.3% of the online audience in India, 62.7% in Russia, 77.3% in Brazil, and 84.1% in China (see Fig. 2).

Looking at the share in global internet reach, *Amazon* is one of the leading E-commerce platforms worldwide, reaching 20.4% of worldwide internet users. Fig. 3 shows the global market reach of the largest online retail and auction sites in June 2011. Immediately

[2] STATISTA (www.statista.com) is the world's largest statistics portal, providing access to relevant data from over 18,000 sources.

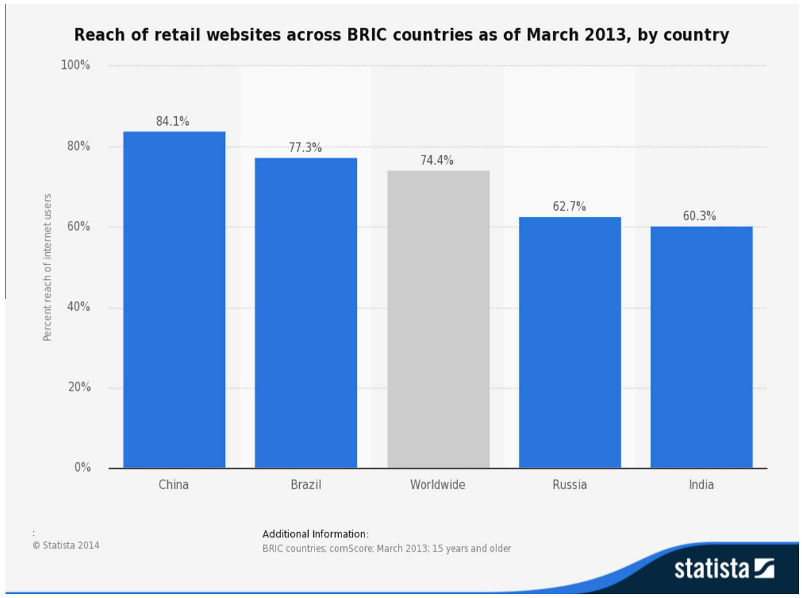

Fig. 2. Reach of retail websites of BRIC countries w.r.t. the worldwide trend.

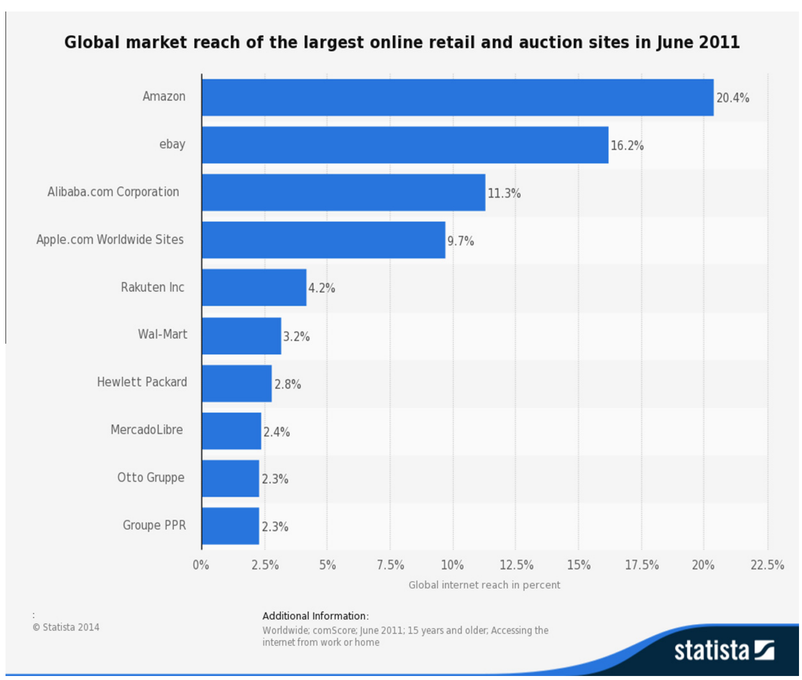

Fig. 3. Retail websites as of June 2011. The first two places are occupied by *Amazon* and *ebay*.

after Amazon the place is occupied by *ebay* auction site, reaching 16.2% of internet users and *Alibaba*, the Chinese corporation, that captures 11.3% of internet users. To follow *Apple* that reaches 9.7% of users worldwide.

It is interesting to note that the most popular retail category worldwide is represented by *consumer electronics* that, as of May 2013, was accessed by 26% of internet users. *Apparel* is at the second place, accessed by 24% of users. Fig. 4 illustrates the top ten worldwide retail categories by reach of internet audience as of May 2013. The first two retail categories inspired the choice of the datasets used in the experimental part of this paper that analyzed the sentiment polarity of users reviews for smartphones and fashion belonging respectively to the first and second most important retail categories. In particular, our interest scrutinized datasets extracted from Facebook posts of Nokia, Zalando and Privalia three well known companies. Nokia declining share of its global mobile market to us represents a strength for our purposes since our attempt to capture users' sentiment about Nokia smartphones would be beneficial for the Finnish company, previously a clear market leader, that would try to improve its products following users' suggestions.

On the other hand, our interest for Zalando is imposed exactly by the success reached by the fashion e-retailer that in 2013 generated more than 1.76 billion euros in revenues, up from 1.16 billion euros in 2012, putting itself as first German-based internet company and one of the biggest worldwide.[3]

[3] http://www.statista.com/statistics/310587/biggest-global-internet-companies/.

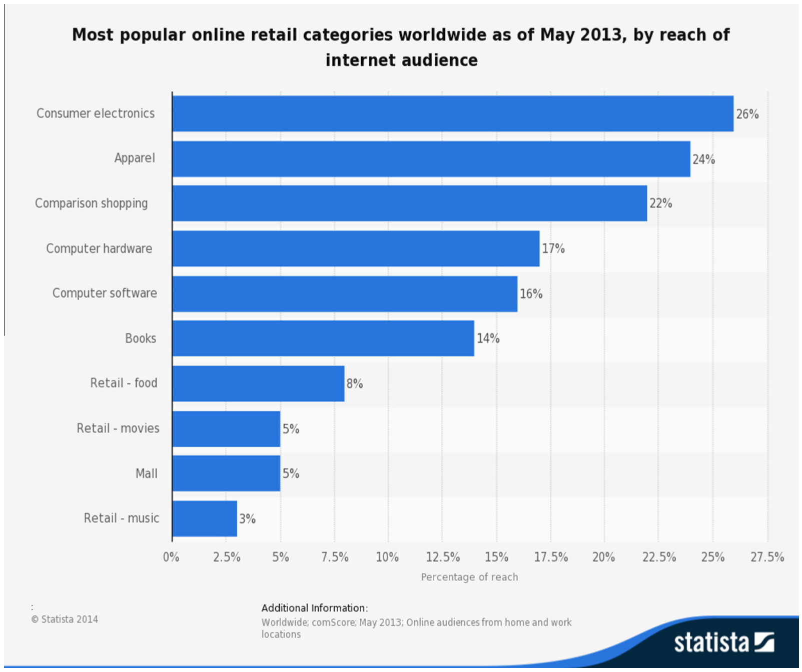

Fig. 4. Popular retail categories as of May 2013. The top two categories inspire the choice of the datasets explored in the experimental part of this paper.

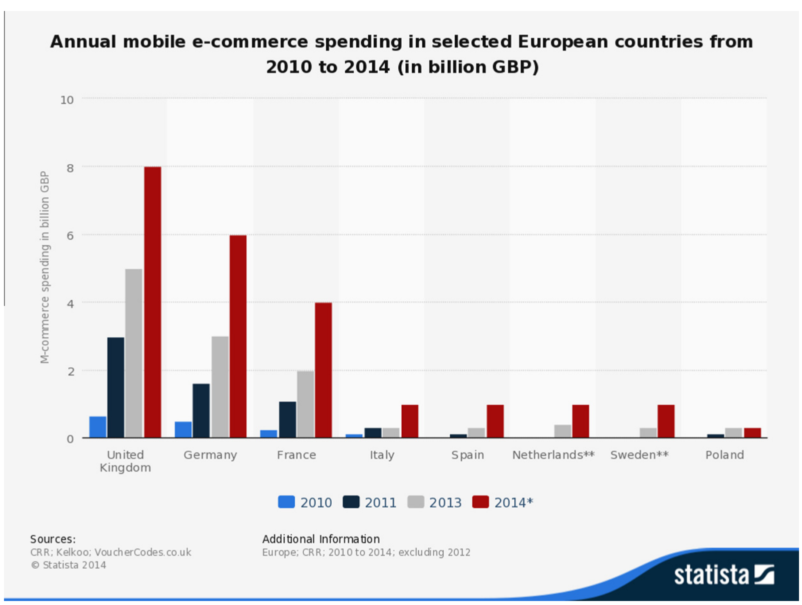

Fig. 5. Mobile E-commerce expenditure expressed in billion GBP. The rank is leaded by UK and Germany, followed by France whose expenditure in mobile E-commerce increased more than fifteen times on the last four years.

With customers increasingly using their mobile devices for various online shopping activities, mobile shopping has been on the rise considering that, currently, more than 57 million people in the United States are mobile buyers, using their tablets, smartphones and other connected devices to shop online. For instance, in 2012, U.S. on one's own mobile commerce revenue amounted to approximately 10 billion U.S. dollars, and are estimated to reach 17 billion U.S. dollars in 2014. The annual E-commerce spending in European countries as well demonstrates that also in Europe investments in the mobile channel promises increasing revenues. As shown in Fig. 5 all European countries analyzed by STATISTA grow yearly in their mobile budget. The top end of the table is leaded by United Kingdom and Germany whose mobile spending increased tenfold from 2010 to 2014. France occupies the position immediately after in the rank. Its annual mobile spending, even though lower in absolute value, it is increased more than fifteen times on the last four years. On the whole, expert projections estimate that, in Europe, 13% of the entire online sales will produced via smartphones and tablets. As shown in Fig. 6 a gap exists among The North and The South since the top end of the rank is leaded by UK, Germany, and Sweden, while France, Italy and Spain occupy the lowest-ranking. However, the analysis shows a common increasing ratio.

Up to now, it has been introduced the growth of online marketplace and its positive aspects, in terms of revenues, for the seller side. The other side of the coin is represented by the key role

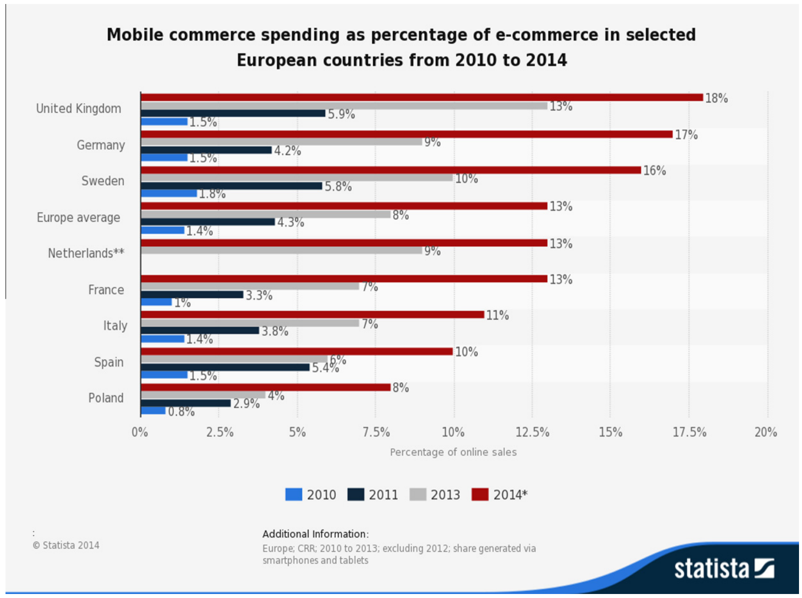

Fig. 6. Mobile E-commerce spending as a percentage of E-commerce spending in selected countries in Europe from 2010 to 2013, with a forecast to 2014. Figure unequivocally shows a gap existing among The North and The South of Europe.

played by the buyer and her/his degree of acceptance of online shopping that is making this marketplace so growing and prosperous.

Fig. 7 reports, in millions, the number of digital shoppers in U.S. from 2010 to 2018. Digital shoppers are online users who have browsed, researched or compared products online via any device within the past year but not have necessarily bought digitally. For instance, STATISTA reports that in 2013 191.1 million U.S. citizens were online shoppers and had browsed products, compared prices or bought merchandise online at least once. An interesting aspect is illustrated in Fig. 8, showing the share of digital shoppers in the U.S. who have made purchases via *webrooming* or *showrooming*. It seems that 78% of U.S. digital shoppers bought a product at a store after browsing digitally and, viceversa, 72% of them bought a product digitally after browsing at a store. These data show that a bidirectional channel exists between the brick-and-mortar of the traditional marketplace and the online one. Among digital shoppers in U.S., 17% of them declared themselves to be occasional online shoppers and 19% declared themselves to be rational online shoppers. Actually, the problem of *rational* vs. *non-rational* buyer behavior raised debate and experiments. For instance, Oulasvirta et al. (2009) demonstrated that the *paradox of choice* holds on web choices as well. In such a situation, that involves uncertainty, people rely more on *heuristics* than rationality to arrive at decisions and purchases, and if the seller implements on her/his website services able to ease the shopping activity this would be beneficial for the buyer and the *digital shopper* may easily become a *digital buyer* every inch. Seeing the number of digital buyers[4] worldwide and the projection for the years to come shown in Fig. 9, this means more revenue for the seller and a more satisfaction for the buyer while shopping online.

Development of more stable and reliable online platforms has improved online shopping significantly. As already said above, community put a lot of effort for developing Web/shopping decision support systems that may help buyers finding the most relevant information (Resnick & Varian, 1997; Turban et al., 2007; Xiao & Benbasat, 2007), spawning a lot of interdisciplinary interest (Alba et al., 1997; HŁubl & Trifts, 2000; HŁubl & Murray, 2003; Kowatsch & Maass, 2010; Lee & Lee, 2009; Murray & HŁubl, 2009; Qiu & Benbasat, 2010; Wang & Doong, 2010). For instance, along the line that paved *rational* vs. *non-rational* shopping behaviors, cognitive scientists (Newell & Simon, 1976; Oulasvirta et al., 2009) debate on the role that individual factors, together with external information, play in the decision making process and there is a growing number of studies focusing on the enhancing of buyers online shopping decision with the aim to improve their subjective attitudes towards shopping decisions (Gupta & Harris, 2010; Kukar-Kinney & Close, 2010; Lee & Lee, 2004, 2009). These services can be implemented using decision strategies, i.e., rules, either referred to as *heuristics* (Marewski et al., 2010; Pearl, 1984; Polya, 1945), or *rules of thumb* (Gigerenzer, 2007; Waksberg et al., 2009), employed by individuals to arrive at decisions and purchases (Hogarth, 1987; Jedetski et al., 2002).

Araa and Len (2009) indicated the strategy's dichotomy *rational* vs. *non-rational* introduced above as the distinction between *compensatory* (i.e., rational/normative) and *non-compensatory* purchasing strategies (i.e., heuristics). For instance, a website service allowing the buyer to enter *text for searching*, or for choosing from a list of criteria (e.g., *shopping by categories* or *by price*), are implementations of *non-compensatory strategies*. On the other hand, a website displaying an array of rows of products with columns for various attributes is an example of *compensatory strategy* that allows buyers to examine several attributes for several products at a time.

Heavily based on this debate, and using this background, D'Avanzo and Kuflik (2013) pointed to a gap that exists among sellers services and buyers expectations, suggesting that it can be bridged turning to *non-compensatory strategies*. The analysis of the services provided by 594 E-commerce websites showed a list of 68 different variants of services offered by them. As an example for a general service we can take *product selection*, representing a typical non-compensatory strategy set, which was further refined to service variants such as *product selection by categories*, *types*, *prices*, *brands*, *sales percentage* and *alphabetical order*. After getting an idea about the various services provided by E-commerce websites, authors turned to potential buyers[5] and tried to understand,

[4] STATISTA consider digital buyers as internet users who have made at least one purchase via any digital channel within the past year, including online, mobile and tablet purchases.

[5] *Potential buyers* are *digital buyers* as considered by STATISTA and described in a previous footnote.

Fig. 7. The graph refers to the number of digital shoppers in U.S. from 2010 to 2018.

Fig. 8. The graph reports on the share of digital shoppers that made purchases either via webrooming or showrooming.

through the publishing of an online questionnaire, what services they perceive as relevant. The questionnaire, containing 37 statements, asked users to state their opinion about services found using a 5-points Likert scale. The questionnaire was published online for a few weeks and answered by 165 users, 107 males and 58 females. 7 of them under the age of 21, 60 between 21 and 29, 41 between 30 and 39, 33 between 40 and 49 and 24 are above 50. Fig. 10 shows users' average rate of services compared to the service popularity in websites that offered it.

It is expected that services considered to be relevant to the users (i.e., with high average grade, as appeared in the questionnaires) will be also widely available at the E-commerce websites (i.e., high percentage of websites will offer them). Whenever a gap exists, it means that websites developers/owners probably did not adequately address buyers' needs/expectations. Specifically, Fig. 10 shows that more and more buyers look for non-compensatory strategies implemented as service on sellers websites. These differences were found to be statistical significant in all cases but one (two tailed *T*.Test, $p \prec 0.05$), that is *shop by alphabetical order*. The choosing phase seemed to be the step with the highest diversity. Many different services aimed at helping users find what they need. However, looking at what websites offer and at users expectations, it seems that websites are not supporting enough their users expectations. Users expect much more than what the websites provide. Users mark services as highly important but they are not widely provided, at least not as widely as can be expected by their importance of the users. The gaps are especially evident in everything that relates to *products/user's reviews* and *evaluations*, where users are expecting much more than current websites provide.

The following of this paper aims at providing a real-world framework to deal with the gap existing among buyers'

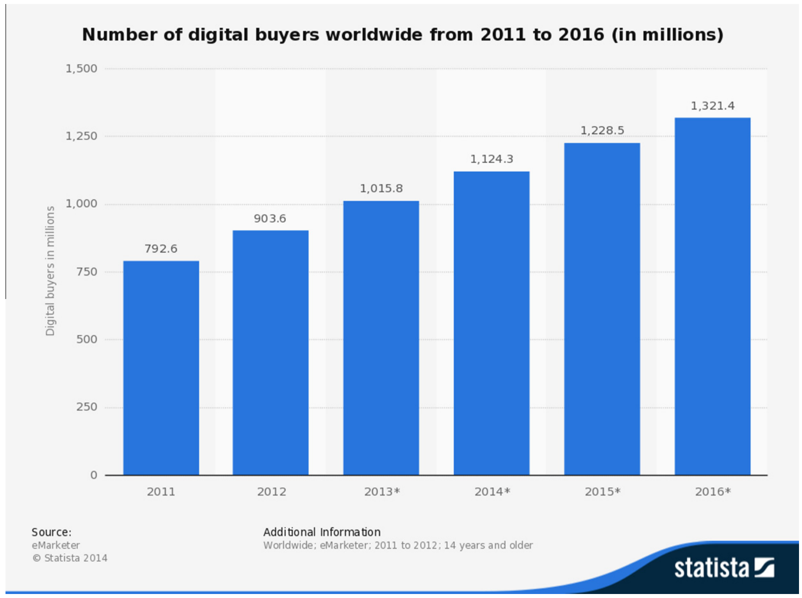

Fig. 9. The graph shows the projection of digital buyers worldwide since 2011 up to 2016 (the numbers reported are in millions).

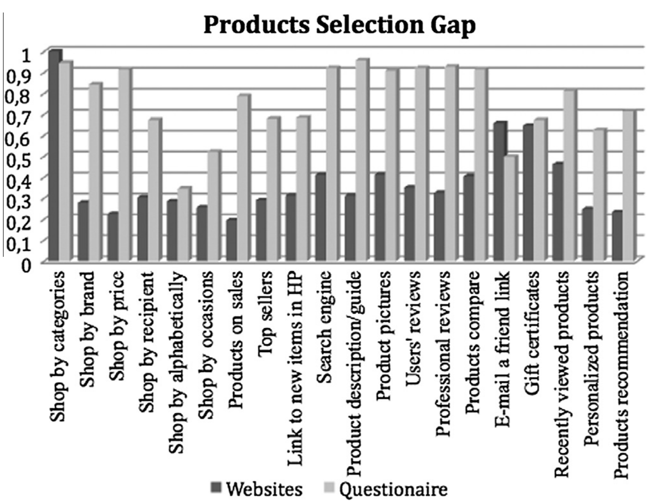

Fig. 10. Services provided by websites during the encounter phase, compared with the importance of these services to the users.

expectations about products'/users' reviews. The experiments introduced are carried out using dataset gathered from Facebook pages of successful and/or declining companies that can, anyway, benefit from these kinds of technique either to improve their offer or to completely change the vision of their product looking at users' feedback about them. As discussed in next section there are many efficient attempts to design and release opinion ming/sentiment analysis frameworks. But, as discussed above, the increasing of E-commerce also stimulated the request of more fine-grained tools able to support buyers in their choices while shopping online.

3. Related applications

Different applications have been proposed in literature regarding sentiment analysis tackled with machine learning approaches and exploiting new media. In the following we briefly recap some of them, selected by looking at the learning approach employed, the feature selection method adopted, and, among a number of applications of these techniques, we privileged the last papers that experimented with reviews topics' similar to ours, in other words those falling under the entertainment market (e.g., fashion, smartphones, electronics, and so on). Never forget, however, that opinion mining demonstrated its efficiency in other domains besides those considered in the following, that, however, are also related with the cognitive background which inspired our approach described in this paper (Dascalu, Bodea, Lytras, De Pablos, & Burlacu, 2014; D'Avanzo, Kuflik, & Lytras, 2008; Moreno-Jimnez, Cardeosa, Gallardo, & De La Villa-Moreno, 2014).

Vinodhini and Chandrasekaran (2014) propose a hybrid machine learning methodology, exploiting an ensemble of classifiers, to categorize the customer's opinion into positive or negative review. The method employs both a bagging and Bayesian models, each one combined with the Principal Component Analysis as a feature reduction technique. Another attempt of this work is to inquiry the effect of different types of features (i.e., unigram, bigram, trigram) that can be employed to build the system. Results evaluated in terms of *misclassifications rate*, *correctness*, *completeness and effectiveness*, showed an improvement with respect to Logistic Regression and Support Vector Machines methods in classifying positive and negative opinions. In particular, among the different types of feature set employed, the best performance is obtained using a combination of unigram, bigram, and trigram.

Kim, Choi, Hwang, and Kim (2014) proposed a supervised learning approach, based on Support Vector Machines, in order to classify products according to their attributes. For instance, the methodology allows finding a positive or negative opinion on a mobile phone by using *camera*, *sound*, *keypad*, and *battery* as features and Display, Network, AP, Size, Camera, and Audio as six predefined classes/sub-categories. The proposed approach predicts a particular attribute and the overall product according to the user perception. The paper introduces also the use of a domain dictionary made of about 500 words, weighted from -5 to $+5$ for each sentiment word, extracted from more than 5000 online reviews (e.g., amazon.com). The proposed method seems to suffer by the employing of domain-specific dictionaries requested to analyze any kind of product matter of interest.

Dalal and Zaveri (2014) exploit fuzzy functions in the sentiment classification task to emulate the effect of different linguistic hedges (i.e., *modifiers*, *concentrators*, and *dilators*), with the aim of classifying both binary and fine-grained sentiments of users' reviews. At the early stage, the approach turn to SentiWordnet to identify the initial sentiment value of an opinionated phrase, assigning them a triple sentiment orientation (i.e. positivity/ objectivity/ negativity). In the following steps, if/when hedges are observed, the sentiment may be modified using fuzzy functions. For instance, according to the approach, a sentence extracted from a smartphone's review, such as "the body is fragile", will receive an initial score thanks to the only use of SentiWordnet. But if the descriptor is preceded by a concentrator linguistic hedge (e.g., "very fragile"), then the sentiment score will be modified thanks to the fuzzy score. The procedure was evaluated using a dataset of about 3000 user-generated products reviews for different brands (e.g., tablets, e-book readers, smartphone, and laptops), using reviews scored by 1–5 stars ratings. To the authors, results obtained show that the linguistic hedge approach outperforms other approaches when the granularity of the task increases.

Choi, Lee, Park, and Na (2013) approached the problem of sentiment analysis/opinion mining offering a systematic procedure that analyzes a large amount of data (i.e., 39 GB), collected from Korean review sites. The procedure makes though-out use of standard techniques both from the Information Retrieval arena (i.e., focused web crawlers to retrieve data) and from Natural Language Processing (NLP) techniques that, in turn, inspired the sentiment analysis part of experiments. Besides, an efficient use of database storage and retrieval makes the rest. The crawler gathers all useful information from websites (i.e., *product category*, *subcategory*, *name specification*) for later sentiment analysis. The core of the whole mechanism is made of a cascade fashioned morphological analyzer, consisting of three steps: a text pre-processing, a real morphological analysis, and a Part of Speech tagging step. The authors also constructed a synonyms table since a number of them are used in the Web reviews (e.g., "Galnot" in place of "Galaxy note"). All this material (i.e., database of abbreviations, synonyms, acronyms, slangs, and so on), along with adjective words, constitute a tuple of five components that represented on a graph using different categories returns the whole user's sentiment. Experimental results carried out using a huge dataset show a correctness of about 73% in classifying positive/negative sentences.

4. Polarity detection through Bayesian approach

In order to extract significative features and to detect polarity in comments posted on social networks, we explored well consolidated approaches present in literature (Liu, 2010, chap. 28; Vinodhini & Chandrasekaran, 2012; Turney & Littman, 2003). We have privileged the simplicity of the approach in order to explore the possibility of applying such techniques also for comments written in Italian language (Mazzonello, Gaglio, Augello, & Pilato, 2013; Sangiorgi, Augello, & Pilato, 2014).

4.1. Feature analysis

The feature analysis procedure exploits a dataset containing a set of short documents (e.g. posts or comments in a social network) expressing an opinion or not.

The terms in the posts are then processed through an Italian language stemmer in order to consider terms independent from the grammatical gender and number variations; besides, if a term is preceded by the Italian word "non" (which means "not" in English), the term is joined with the negation and it is considered a new word. For example the term "funziona" ("it works") is stemmed as "funzion", while the sequence "non funziona" ("it doesn't work") is considered as one single term identified by the new word "non_funzion".

Subsequently, the procedure collects all posts expressing positive opinions in one single *polarity document*. The same thing is done for the negative posts and for the neutral ones. As a consequence, we obtain three polarity documents, each one labeled with a polarity class, containing all coherent posts. The method then extracts from these three polarity documents the terms that could be considered as features.

In particular, the Term Frequency–Inverse Document Frequency (TFIDF), which is a well known weighting measure often used in information retrieval, was adapted for managing the case of polarity detection. We called this weighting scheme TF–IPF (Term Frequency–Inverse Polarity Frequency). It returns a selection of the most relevant terms for each polarity class, where the relevance of a term is strictly connected with its semantic polarity.

In our approach the TF_i term measures how frequently a term t occurs in the i-th polarity document, while the Inverse Polarity Frequency measures how much important a term is for that class.

$$TF_i(t) = \frac{\textit{Number of times the term t appears in the polarity document i}}{\textit{Number of terms in the polarity document i}} \tag{1}$$

$$IPF(t) = \log_e\left(\frac{\textit{Number of polarity documents}}{\textit{Number of polarity documents containing the term t}}\right) \tag{2}$$

The polarity score $s_i(t)$ where $i = 1, 2, 3$ (i.e. *positive, negative, neutral*) associated with the term t for the polarity document i is therefore:

$$s^{class_i}(t) = TF_i(t) \cdot IPF(t) \tag{3}$$

As a consequence, the terms having the highest $s(t)$ are good candidate features, particularly characterizing the polarity of a chunk of text. A threshold is experimentally determined in order to retain the most significative words.

4.1.1. Naïve Bayes Classifier

Naïve Bayes Classifiers are classifiers based on the Bayes' theorem. They assume independence between the features and they can be trained very efficiently, according to the supervised learning paradigm. This methodology has been effectively used in different, complex real-world applications, and it has been widely used in text categorization.

The aim is to determine the class c_i from the probability that the document d, expressed as a set of m features f_i (where $i = 1, \ldots, m$) belongs to that class $p(c_i|d)$, given by:

$$p(c_i|f_1, f_2, \ldots, f_m) = \frac{1}{A} p(c_i) \prod_{k=1}^{m} p(f_k|c_i) \tag{4}$$

where A is a normalization factor, and $p(f_k|c_i)$, is the probability that the features belong jointly to the class c_i:

$$p(f_k|c_i) = \frac{N(F_k = f_k \cup C = c_i)}{N(C = c_i)} \tag{5}$$

We have used this standard machine learning approach in order to determine the sentiment of posts in social networks.

5. Experimental results

Users typically interact with a Facebook business page in order to show their fidelity to the brand, to find out new offers, to claim, to receive assistance or simply to show their endorsement to the brand or company.

Since E-commerce and social network platforms like Facebook are merging (many of the users visiting an E-commerce website signs in with its own Facebook credentials), automatically analyzing the comments that are being published by the users as replies to the posts that a company writes on its Facebook page plays an essential role in customer satisfaction (or both explicit or implicit desires) detection.

However, analyzing the comments on Facebook pages is an extremely challenging task, since:

- They are often very concise: even single-word.
- Only few times they are more detailed and resemble a review.
- Comments are often 'off-topic', just saying that a competitor is better without any connection with the original post where the comment was left.
- Comments are often mere spam, such as people that only want to sponsor their page by posting a link, or chain-jokes.
- Many times, people start to flame themselves, resulting a discussion that does not involve the brand but just answers among users themselves.
- The same positive words can be spent for the brand that owns the page or for competitors: this makes it difficult to build a lexicon with positive and negative words.
- There are a lot of misspellings and orthographical mistakes.
- Many comments are sarcastic.

A way to analyze the sentiment in the comments of the Facebook page could be the construction of a dataset of users' comments, in Italian language, in order to use it as a training set in a supervised approach. We have focused our analysis on three case studies: *Nokia, Zalando* and *Privalia* Italian Facebook pages.

- *Nokia* is one of the most interesting brands in the smartphone market. Nokia appears in the top Facebook pages for new fan number and even in response-time rank: this means a great attention by Nokia to renew its brand image showing itself to be fresh and competitive.
- *Zalando* is an E-commerce company founded in 2008, and established in Italy in 2011. In 2012 it has been the most clicked fashion-oriented E-commerce marketplace. Now it is considered a leader company in the field of shoes and fashion. The company extensively exploits social networks in order to promote its business.
- *Privalia* is a club that organizes discounted sales (up to 70% with respect to the retail standard prices). Members of this club receive daily offers. The company has been established in 2006. It is on Facebook since 2009 and it has more than 4 million fans all over the world.

We extracted a number of comments to posts published on each of these aforementioned companies and for each one of them, we examined them and labeled their polarity as being *positive, negative, or neutral.*

5.1. Features analysis of Nokia dataset

For the Nokia Dataset we have collected the posts and their comments published on the Nokia's official Facebook page from the 15 to the 28 of may 2013. We therefore gathered 22 Nokia's posts, with a total number of 20867 "likes", and 1003 comments, with a total number of 1268 "likes" to these comments.

The comments were manually tagged as being positive, negative or neutral by considering the Nokia point of view: if a comment was tagged as being negative, this does not mean that we will find negative opinions, as the comment may also refer very positively to a Nokia's competitor. All the typical expressions, also referred to the features of the smartphones, that users use to express their positive or negative opinion toward Nokia were tagged in the same way.

The resulting dataset we built is composed of three polarity documents, each one of them containing respectively:

- 378 positive tagged comments,
- 357 negative tagged comments,
- 268 neutral tagged comments.

After performing a stemming of Italian words with an ad hoc algorithm, we extracted from the dataset the stemmed terms that could have been considered as features, in particular we used the score $s_i(t)$ computed as Term Frequency–Inverse Polarity Frequency (TF*IPF) weighting schema illustrated in the previous section.

We have also considered the case of a word preceded by the term "non", which in Italian expresses the negation: for this reason the words "bello" (nice) and "non_bello" (not nice) are being considered two different terms.

Running the algorithm with Nokia's Facebook comments dataset and a threshold of 0.5, we get a list of 214 words which may be strongly related to the identification of a polarity.

For the negative case, we obtained 99 words, including terms (in Italian language) like: *vergogn, non_funzion, matton, non_piac, brutt, schif, photoshop* (i.e. in English *shame, doesn't_work, brick, doesn't_like, ugly, loathing, photoshop*). These words are actually relevant for the classification purpose since they imply real negative opinions most of the times.

One interesting thing to point out is that the word "photoshop" which may seem, at a first glance, a mistake of the TF–IPF weighting score. It could actually be considered a word that implies negativity since it occurs when users blame the post writer of the Facebook page for retouching the photo that appears in that post.

For the positive terms, we obtained 115 words, among which: *fantast, ottim, divin, veloc, design, bomb, zeiss* (in English *fantastic, great, divine, fast, design, bomb, zeiss*.

These words are actually relevant for the classification purpose since they imply real positive opinions most of the times. Let us consider also that the word "zeiss" which may seem, at first glance, a mistake of the TF–IPF weighting score. It could actually be considered a word that implies positivity since it occurs when users want to highlight the high quality of the camera compartment which uses the Zeiss optics. The same observation can be done with the word "bomb" which is a jargon meaning " it is very good, outstanding".

5.2. Identification of polarity scores in Zalando and Privalia comments to posts

For the Zalando Facebook page, we have gathered data coming from 39 posts from February 2014 to March 2014. We have collected 485 comments, 863 sharings, 12927 "likes".

The resulting dataset we built is composed of:

- 48 positive tagged comments,
- 27 negative tagged comments,
- 27 neutral tagged comments.

For the Privalia Facebook page, we have gathered data coming from 31 posts from February 2014 to March 2014. We have collected 367 comments, 583 sharings, 9875 "likes".

The resulting dataset we built is composed of:

- 55 positive tagged comments,
- 31 negative tagged comments,
- 15 neutral tagged comments.

Since the number of comments is not sufficient to guarantee good performances of the classifier, we merged the two "fashion" oriented datasets, obtaining three polarity documents, each one of them containing:

Table 1
Precision, Recall, True Negative Ratio and Accuracy for the Italian comments regarding Zalando and Privalia Facebook Pages.

Class	Precision	Recall	True Negative Ratio	Accuracy
Positive	0.55	0.86	0.30	0.58
Negative	0.16	0.55	0.71	0.70
Neutral	0.14	0.10	0.86	0.72

Table 2
Precision, Recall, True Negative Ratio and Accuracy for the automatically translated comments regarding Zalando and Privalia Facebook Pages.

Class	Precision	Recall	True Negative Ratio	Accuracy
Positive	0.67	0.79	0.58	0.69
Negative	0.52	0.50	0.80	0.71
Neutral	0.11	0.05	0.89	0.72

- 103 positive tagged comments,
- 58 negative tagged comments,
- 42 neutral tagged comments.

In this case, we have used a general-purpose lexicon of positive/negative Italian words as features for a Naïve Bayesian classifier, already trained on a generic dataset, obtaining the following results for each class (Table 1).

In order to compare the classification capabilities, we have automatically translated the comments in the dataset through the use of Google Translator, and re-executed the experiments with the same methodology (with a pre-trained Naïve Bayesian Classifier on Janyce Wiebe's subjectivity lexicon (Riloff & Wiebe, 2003)), obtaining the following results (Table 2).

We can observe that the translation has no effect on accuracy of negative or neutral class, while there is a significative improvement of the positive class.

6. Conclusions

This paper provided a real-world framework to deal with the gap existing among buyers' expectations about products'/users' reviews (D'Avanzo & Kuflik, 2013). To this end we borrowed a well-known model from *collaborative learning*, emulating a situation in which two or more people learn or attempt to learn something together (Bruffee, 1993). In this sense buyers engaged in the online shopping capitalize on one another's resources and skills just turning to the Bayesian social sentiment analysis tool proposed, cooperatively exploiting one another for opinion, in order to make her/his decisions.

The introduced procedure mines users opinions from specific kinds of markets, visually summarizing them, in order to alleviate buyers overload and speeding up her/his shopping activity.

The introduced experiments are carried out using datasets gathered from Facebook pages of successful and/or declining companies that can, anyway, benefit from these kinds of technique, either to improve their offer, or to completely change the vision of their product looking at users' feedback about them.

Acknowledgements

This work has been partially supported by the MIUR PON01 01687 – SINTESYS Research Project.

We kindly thank our graduate and undergraduate students for their support.

References

Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., et al. (1997). Interactive home shopping: Consumer, retailer, and manufacturer incentives to participate in electronic marketplaces. *The Journal of Marketing, 61*(3), 38–53.
Araa, J. E., & Len, C. J. (2009). Understanding the use of non-compensatory decision rules in discrete choice experiments: The role of emotions. *Ecological Economic, 68*(8–9), 2316–2326.
Bruffee, K. (1993). *Collaborative learning*. Baltimore: The Johns Hopkins University Press.
Cheng, J., Sun, A., & Zeng, D. (2010). Information overload and viral marketing: Countermeasures and strategies. *Advances in Social Computing, Lecture Notes in Computer Science, 6007*, 108–117.
Chiu, M. M. (2000). Group problem solving processes: Social interactions and individual actions. *Journal for the Theory of Social Behavior, 30*(1), 27–50. 600–631.
Choi, C., Lee, J., Park, G., & Na, J. (2013). Voice of customer analysis for internet shopping malls. *International Journal of Smart Home, 7*(5), 291–304.
Dalal, M. K., & Zaveri, M. A. (2014). Opinion mining from online user reviews using fuzzy linguistic hedges. *Applied Computational Intelligence and Soft Computing, 2014*, 9. http://dx.doi.org/10.1155/2014/735942. Article ID 735942.
Dascalu, M.-I., Bodea, C.-N., Lytras, M., De Pablos, P. O., & Burlacu, A. (2014). Improving e-learning communities through optimal composition of multidisciplinary learning groups. *Computers in Human Behavior, 30*(January), 362–371.
D'Avanzo, E., & Kuflik, T. (2013). E-commerce websites services versus buyers expectations: An empirical analysis of the online marketplace. *International Journal of Information Technology & Decision Making, 12*(04), 651–677.
D'Avanzo, E., Kuflik, T., & Lytras, M. D. (2008). Building and using domain ontologies for learning in various domains: A semantic web-based learning perspective. *International Journal of Knowledge and Learning.*, 329–348. ISSN:1741-1009.
Drigas, A., & Leliopoulos, P. (2013). Business to consumer (B2C) e-commerce decade evolution. *International Journal of Knowledge Society Research (IJKSR), 4*(4), 1–10. http://dx.doi.org/10.4018/ijksr.2013100101.
Gigerenzer, G. (2007). *Gut feelings: The intelligence of the unconscious*. New York: Viking.
Gonzlez-Gonzlez, I., Serradell-Lpez, E., & Castillo-Merino, D. (2012). The implementation of process management: A system to increase business efficiency – Empirical study of spanish companies. *International Journal of Knowledge Society Research (IJKSR), 3*(1), 14–25. http://dx.doi.org/10.4018/ijksr.2012010102.
Gopnik, A., Glymour, C., Sobel, D. M., Schulz, L. E., Kushnir, T., & Danks, D. (2004). A theory of causal learning in children: Causal maps and Bayes nets. *Psychological Review, 111*(1), 3–32.
Gudigantala, N., Song, J., & Jones, D. R. (2008). How well do e-commerce web sites support compensatory and non-compensatory decision strategies? An exploratory study. *International Journal of E-Business Research, 4*(4), 43–57.
Gupta, P., & Harris, J. (2010). How e-WOM recommendations influence product consideration and quality of choice: A motivation to process information perspective. *Journal of Business Research, 63*(9–10), 1041–1049.
HŁubl, G., & Murray, K. (2003). Preference construction and persistence in digital marketplaces: The role of electronic recommendation agents. *Journal of Consumer Psychology, 13*(1), 75–91.
HŁubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science, 19*(1), 4–21.
Hogarth, R. (1987). *Judgment and choice*. New York: John Wiley and Sons.
Iyengar, S. S., Wells, R. E., & Schwartz, B. (2006). Doing better but feeling worse: Looking for the "best" job undermines satisfaction. *Psychological Science, 17*(2), 143–150.
Jedetski, J., Adelman, L., & Yeo, C. (2002). How web site decision technology affects consumers. *IEEE Internet Computing, 6*(2), 72–79.
Karr-Wisniewski, P., & Lu, Y. (2010). When more is too much: Operationalizing technology overload and exploring its impact on knowledge worker productivity. *Computers in Human Behavior, 26*(5), 1061–1072.
Kim, J., Choi, D., Hwang, M., & Kim, P. (2014). Analysis on smartphone related twitter reviews by using opinion mining techniques. In J. Sobecki, V. Boonjing, & S. Chittayasothorn (Eds.), *Advanced approaches to intelligent information and database systems, studies in computational intelligence* (Vol. 551, pp. 205–212).
Kowatsch, T., & Maass, W. (2010). In-store consumer behavior: How mobile recommendation agents influence usage intentions, product purchases, and store preferences. *Computers in Human Behavior, 26*(4), 697–704.
Kukar-Kinney, M., & Close, A. G. (2010). The determinants of consumers online shopping cart abandonment. *Journal of the Academy of Marketing Science, 38*(2), 240–250.
Lee, B. K., & Lee, W. N. (2004). The effect of information overload on consumer choice quality in an on-line environment. *Psychology and Marketing, 21*(3), 159–183.
Lee, G., & Lee, W. J. (2009). Psychological reactance to online recommendation services. *Information & Management, 46*(8), 448–452.
Lee, C. D., & Smagorinsky, P. (Eds.). (2000). *Vygotskian perspectives on literacy research: Constructing meaning through collaborative inquiry*. Cambridge, England: Cambridge University Press.

Lin, C. T., Hong, W. C., Chen, Y. F., & Dong, Y. (2010). Application of salesman-like recommendation system in 3G mobile phone online shopping decision support. *Expert Systems with Applications, 37*(12), 8065–8078.
Liu, B. (2010). Sentiment analysis and subjectivity. In N. Indurkhya & F. J. Damerau (Eds.), *Handbook of natural language processing* (2nd ed.).
Lytras, M. D., & de Pablos, P. O. (2011). Software technologies in knowledge society. *Journal of UCS, 17*(9), 1219–1221.
Marewski, J. N., Schooler, L. J., & Gigerenzer, G. (2010). Five principles for studying people's use of heuristics. *Acta Psychologica Sinica, 2010 42*(1), 72–87.
Mazzonello, V., Gaglio, S., Augello, A., & Pilato, G. (2013). A study on classification methods applied to sentiment analysis. In *IEEE sixth international conference on semantic computing* (pp. 426–431).
Mohanty, R., Ravi, V., & Patra, M. R. (2010). Web-services classification using intelligent techniques. *Expert Systems with Applications, 37*(7), 5484–5490.
Moreno-Jimnez, J. M., Cardeosa, J., Gallardo, C., & De La Villa-Moreno, M. A. (2014). A new e-learning tool for cognitive democracies in the knowledge society. *Computers in Human Behavior, 30*(January), 409–418.
Murray, K. B., & HŁubl, G. (2009). Personalization without interrogation: Towards more effective interactions between consumers and feature-based recommendation agents. *Journal of Interactive Marketing, 23*(2), 138–146.
Newell, A., & Simon, H. A. (1976). Computer science as empirical inquiry: Symbols and search. *Communications of the ACM, 19*(3), 113–126.
Oulasvirta, A., Hukkinen, J. P., & Schwartz, B. (2009). When more is less: The paradox of choice in search engine use. In *Proceedings of the 32nd international ACM SIGIR conference on research and development in information retrieval, July, 2009* (pp. 516–523). Boston, MA.
Papatla, P., & Liu, F. O. (2009). Google or BizRate? How search engines and comparison sites affect unplanned choices of online retailers. *Journal of Business Research, 62*(11), 1039–1045.
Pearl, J. (1984). *Heuristics: Intelligent search strategies for computer problem solving*. Boston, MA: Addison-Wesley Longman Publishing Co., Inc.
Polya, G. (1945). *How to solve it: A new aspect of mathematical method*. Princeton, NJ: Princeton University Press.
Qiu, L., & Benbasat, I. (2010). A study of demographic embodiments of product recommendation agents in electronic commerce. *International Journal of Human–Computer Studies, 68*(10), 669–688.
Resnick, P., & Varian, H. R. (1997). Recommender Systems. *Communications of the ACM, 40*(3), 56–58.
Riloff, E., & Wiebe, J. (2003). Learning extraction patterns for subjective expressions. In *Conference on empirical methods in natural language processing (EMNLP-03). ACL SIGDAT* (pp. 105–112).
Russo, J. E. (1974). More information is better: A reevaluation of Jacoby. *Journal of Consumer Research, 1*(3), 68–72.
Sangiorgi, P., Augello, A., & Pilato, G. (2014). An approach to detect polarity variation rules for sentiment analysis. In *Proc of WEBIST 2014 – 10th international conference on web information systems and technologies, 3–5 April, 2014*. Barcelona, Spain.
Sicilia, M., & Ruiz, S. (2010). The effects of the amount of information on cognitive responses in online purchasing tasks. *Electronic Commerce Research and Applications, 9*(2), 183–191.
Simon, H. (1956). Rational choice and the structure of the environment. *Psychological Review, 63*(2), 129–138.
Toncovich, A., Turn, A., Escobar, M. T., & Moreno-Jimnez, J. M. (2011). A quantitative approach to identify the arguments that support decisions in e-cognocracy. *International Journal of Knowledge Society Research (IJKSR), 2*(3), 36–48. http://dx.doi.org/10.4018/jksr.2011070104.
Turban, E., Aronson, J. E., Liang, T. P., & Sharda, R. (2007). *Decision support and business intelligence systems* (8th ed.). NJ: Prentice Hall.
Turney, P. D., & Littman, M. L. (2003). Measuring praise and criticism: Inference of semantic orientation from association. *ACM Transactions on Information Systems, 21*, 315–346.
Tversky, A., & Kahneman, D. (1990). Judgment under uncertainty: Heuristics and biases. In G. Shafer & J. Pearl (Eds.), *Readings in uncertain reasoning* (pp. 32–39). San Francisco, CA: Morgan Kaufmann Publishers.
Vinodhini, G., & Chandrasekaran, RM. (2012). Sentiment analysis and opinion mining: A survey. *International Journal of advanced Research in Computer Science and Software Engineering, 2*(6).
Vinodhini, G., & Chandrasekaran, R. M. (2014). Measuring the quality of hybrid opinion mining model for e-commerce application. *Measurement, 55*, 101–109.
Waksberg, A. J., Smith, A. B., & Burd, M. (2009). Can irrational behaviour maximise fitness. *Behavioral Ecology and Sociobiology, 63*(3), 461–471.
Wang, H., & Doong, H. (2010). Online customers' cognitive differences and their impact on the success of recommendation agents. *Information and Management, 47*(2), 109–114.
Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly, 31*(1), 137–209.