Association for Information Systems

AIS Electronic Library (AISeL)

ICIS 2019 Proceedings

Analytics and Data Science

Trust and Distrust in Big Data Recommendation Agents

Heverton Roberto de Oliveira Cesar de Moraes
Fundacao Getulio Vargas, heverton.rmoraes@gmail.com

Otavio Sanchez
Fundacao Getulio Vargas - FGV, otavio.sanchez@fgv.br

Susan Brown
University of Arizona, suebrown@eller.arizona.edu

Bin Zhang
University of Arizona, binzhang@arizona.edu

Trust and Distrust in Big Data Recommendation Agents

Completed Research Paper

Heverton Roberto de Oliveira Cesar de Moraes
EAESP-FGV Brazil
heverton.rmoraes@gmail.com

Otavio Sanchez
EAESP-FGV Brazil
otavio.sanchez@fgv.br

Susan Brown
Eller College of Management
University of Arizona
suebrown@eller.arizona.edu

Bin Zhang
Eller College of Management
University of Arizona
binzhang@email.arizona.edu

Abstract

Big data technology allows for managing data from a variety of sources, in large amounts, and at a higher velocity than before, impacting several traditional systems, including recommendation agents. Along with these improvements, there are concerns about trust and distrust in RA recommendations. Much prior work on trust has been done in IS, but only a few have examined trust and distrust in the context of big data and analytics. In this vein, the purpose of this study is to study the eight antecedents of trust and distrust in recommendation agents' cues in the context of the Big Data ecosystem using an experiment. Our study contributes to the literature by integrating big data and recommendation agent IT artifacts, expanding trust and distrust theory in the context of a big data ecosystem, and incorporating the constructs of algorithm innovativeness and process transparency.

Keywords: Trust, distrust, recommendation agent, big data

Introduction

The purpose of this paper is to study the antecedents of trust and distrust in recommendation agents' cues in the context of the Big Data ecosystem. The internet platform evolution, the new technologies for communication and monitoring, as well as the emergence of the social media phenomenon enable the generation, collection and exchange of a vast amount of data from a variety of sources, e.g., mobile devices, sensors, downloaded books, games, sound, and images (Aggarwal 2016). Facebook, for example, the biggest social networking service worldwide, presented more than 1.94 billion global monthly active users, including over close to 1.74 billion mobile monthly active users in the first quarter of 2017 (Statista 2018). On a daily basis, these users share their preferences, opinions, friends, and lifestyles, providing a rich source of information about their behavior and preferences.

Today, recommendation agents (RA) are also challenged to deal with this amount of data to keep providing good recommendations to users. The need for capable product and service RAs, which assist consumers in choosing the "right" products (Ricci and Werthner 2006), is increasing with the variety and quantity of products and services available on the Internet. Now, RAs must include data from external sources such as user's social connection information (e.g., close friends, colleague, schoolmate, influencers, and brands preferences) to boost the elicitation of consumers needs in order to suggest products that best fit consumer interests (Xiao and Benbasat 2007).

Besides the opportunities brought by this new scenario, there are challenges for RAs in providing intelligent recommendations to customers, such as: (1) computing and network efficiency, threatened by the growing need for IS resources due to the individual-centric approach, making it difficult to provide users with timely and suitable recommendations; (2) a lack of objectivity related to social data that include emotional information and may influence the objectivity of the recommendation; (3) sufficiency problems caused by the discontinuous nature of the data collection and sparsity that has become common (Bobadilla et al. 2013); and (4) incomplete knowledge about the social media environment and the lack of trust in internet information (Ghavipour and Meybodi 2017).

Another important challenge is the need for customers to have trust in the RA before using it (Gefen et al. 2003; Komiak et al. 2005; McKnight et al. 2002). However, it is expected that customers present lower levels of trust in systems that function based on a much more complex context and unstructured data. Despite the fact that there are many discussions about trust in the IS literature, only a few address the trust problem in the context of big data and analytics. For example, in a review of papers in the senior scholars' basket of eight top journals in the IS field during the time period of fifteen years, we found 234 papers, with 201 covering trust and 37 covering distrust; the contexts involved security, reliability, regular e-commerce, and the web-based recommendation agent environment (Fang et al. 2015; Komiak and Benbasat 2006, 2008; Komiak et al. 2005; Wang and Benbasat 2005, 2008, 2016). Despite the large number, none of the papers focused on big data and analytics. In the same vein, of 88 papers associated with big data and analytics, only one had a secondary concern about the themes related to trust or distrust (Baesens et al. 2016). Although some prior work has examined trust in RA (Jarvenpaa et al. 2000; Wang and Benbasat 2005; Xiao and Benbasat 2007), the field to date has not addressed this topic in the context of the complexities associated with big data.

Although the big data technology is supposed to enable the evolution of RAs allowing them to process the increased volume and variety of data now available beyond the corporate boundaries (Baesens et al. 2016), it will not be an easy task. Solving the accuracy-diversity problem, as well as gaining enough processing velocity is crucial to fulfill the customers' expectations and build trust. Since the literature has already established the relevance of RA building trust in customers, we chose the big data recommendation agent (BDRA) as the focus of this study, looking at establishing how trust and distrust are shaped in this new and relevant context. Recent studies argue that the context is a critical driver of cognition, attitudes, and behavior, or a moderator of relationships among lower-level phenomena (Bamberger 2008; Hong et al. 2013).

Aiming to fulfill this gap, an experiment with four hundred students was performed to assess the degree of trust and distrust in BDRA. Thus, this study aims to identify the customer recommendation agent trust and distrust antecedents in the context of big data. We simulated the selection of an exchange program (e.g., study abroad), a context in which students usually collect information from many sources like social networks, exchange websites, testimonials, travel agencies, and refer to unstructured information like images and cues from previous users. The relevance of this study relies on the opportunity to validate new factors arising from the big data context that may influence users' trust and distrust in RA suggestions, specially by leveraging two decisive aspects: algorithm innovativeness and process transparency.

Theoretical Background

Distinguishing Big Data Recommendation Agents (BDRA) from Traditional RA

Recommendation agents, also called recommenders systems (RSes), are web-based decision support technologies to assist consumers in their decision-making, decreasing the choice complexity that exists due to the availability of a large set of items (products or services) (Bobadilla et al. 2013; Hennig-Thurau et al. 2012). Beyond helping the customers, the recommendation agents also influence customer preferences and are therefore widely used by firms for retention and promotion purposes (Adomavicius and Tuzhilin 2005).

In the past, the RAs prediction capability was restricted to the companies' information systems. Traditional RAs depended on customer information gathered from customer interactions with the organization's systems or by rare information exchange from business partners (Menon and Sarkar 2016). A typical recommender system uses inputs from people to perform aggregations and directs them to the appropriate set of products or services (Xiao and Benbasat 2007). Among the several algorithms used for product recommendations, the most popular are collaborative filtering and content-based filtering. The collaborative filtering approach determines recommendations by the levels of similarity of preferences of other consumers (Adomavicius and Tuzhilin 2005; Brynjolfsson et al. 2010; Lin et al. 2017). In content-based filtering, new items are recommended based on their similarity to items already present in the user's profile (Adomavicius et al. 2013; Adomavicius et al. 2017; Eirinaki et al. 2018). While guarantying the accuracy of recommendation results these strategies may cause diversity loss (Xu 2019).

The new context of big data has impacted both business and academic fields (Chen et al. 2012). From an enterprise perspective, big data is rebalancing the power of relationships in decision-making for the commercial world (Baesens et al. 2016). New technology available with big data allows business intelligence and analytics to examine high-volume data in order to uncover useful information like hidden patterns, unknown correlations, and others, aiming to help the decision-making processes (Chen et al. 2016). The data in a big data environment are captured from five major sources: (1) large-scale enterprise systems (e.g., enterprise resource planning - ERP, customer relationship management - CRM, supply chain management - SCM, and others); (2) social networks (e.g., Facebook, Twitter, Instagram, Wechat); (3) mobile devices (e.g., geotagging); (4) internet-of-things (e.g., sensors); (5) open/public data (e.g., weather, traffic, maps) (Baesens et al. 2016). New types of web services like REST (representational state transfer) for invoking remote services, JSON (JavaScript object notation) for lightweight data-interchange, allow developers to integrate diverse content from different web-enabled systems (Chen et al. 2012). The data variety is also complemented with the capacity to process a large amount of data with better data flow rate than before (Lycett 2013), moreover, the data about the current context that the customer is might be used into recommendations personalization improving the effectiveness (Malthouse and Li 2017). For example, user actions or events, as indicated by location-based services, might trigger new recommendations (Baesens et al. 2016). Likewise, textual comments in user reviews related to past items, feedback expressed in the form of ratings, or the user's neighborhood using similarities derived from the users' ratings and/or their social relationships can be used to enhance the memory-based collaborative filtering process (Eirinaki et al. 2018).

The RAs algorithms also have evolved with the use of big data technology, allowing new recommender system algorithms that use a huge amount of external data to perform customer opinion processing and text and sentiment analysis, while enabling the execution of various analytical techniques such as association rule mining, database segmentation, and clustering, anomaly detection, and graph mining with different types and sources of data (Chen et al. 2012). For example, Wang et al. (2018b) proposed a new generation of movie recommendation based on a hybrid recommendation model and sentiment analysis on a big data Spark platform to improve the accuracy and timeliness of mobile movie recommender system. The system carries out comprehensive aggregation of user's preferences, reviews, and emotions to help customers to find suitable movies conveniently with both accuracy and timeliness. The solution for the dilemma accuracy-diversity in the traditional collaborative filtering is proposed by Xu (2019) in the big data recommendation agent context by the use of a novel recommendation algorithm based on MapReduce framework, which is a technique associated to big data implementations for processing big data sets with a parallel, distributed method on a cluster.

In Summary, the BDRA can be identified by the origin of the data, if based on transactions versus non-transactions and internal versus external information (Zhao et al. 2014). Therefore, we conceptualize the IT artifact, big data recommendation agent – BDRA, as a new generation of RAs that relies on the information collected from different structured and unstructured sources and processed in the big data for customer and business decision-making. The big data technologies in the RAs perspective represent an opportunity to improve recommendations by monitoring users' behavior and generating value to organizations in the internet, e-commerce, and social media ecosystem (Chen et al. 2012; Chen et al. 2013). Table 1 synthesizes the main differences between the traditional RA and the evolved BDRA.

Dimension	Traditional Recommendation Agent	Big Data Recommendation Agent	Authors
Data Origin	enterprise systems	enterprise systems social networks mobile devices internet-of-things open/public data	(Adomavicius et al. 2017; Baesens et al. 2016)
Data Variety	structured-data (Xu et al. 2014b)	structured data unstructured data *(e.g., text, image, audio, or video data)* contextual data *(e.g., network, weather)*	(Chen et al. 2012; Goes 2014; Malthouse and Li 2017)
Data Volume/Velocity	limited	large volume, MapReduce	(Xu 2019)
Algorithms	collaborative filtering content-based filtering K-Nearest Neighbor diffusion approach	collaborative filtering content-based filtering K-Nearest Neighbor diffusion approach MapReduce multi-objective optimization hybrid recommendation model Sentiment analysis	(Eirinaki et al. 2018; Wang et al. 2018b; Xu 2019)
Algorithm characteristics	accuracy	accuracy/diversity volatility overfit	(Xu 2019)

Table 1. Differences between traditional RA and BDRA

Trust and Distrust

Despite the wide variety of recommendation systems available to end users, the lack of consumer trust prevents the full utilization and benefit of these technologies (Komiak and Benbasat 2006; Thatcher et al. 2011; Vance et al. 2008). Trust is crucial in many of the economic activities that can involve undesirable opportunistic behavior (Fukuyama 1995; Luhmann 2018). In the existing IS literature, trust has typically been conceptualized as a disposition, attitude, belief, intention, or behavior (McKnight and Chervany 2001). According to Gefen et al. (2003), "trust is an expectation that others one chooses to trust will not behave opportunistically by taking advantage of the situation".

For a long time, trust was viewed as the opposite of distrust, used as mutually exclusive and opposite conditions, where trust has been seen as "good" and distrust as "bad" (Cofta 2006; Hsiao 2003; Sztompka 1999). However, Lewicki et al. (1998), in their seminal paper, have theorized that trust and distrust are two distinct constructs that co-exist in an inconsistent state. More recent research has brought empirical evidence that distrust and trust are distinct constructs (Dimoka 2010; Komiak and Benbasat 2008; Lowry et al. 2015). The study by Dimoka (2010), using Functional Magnetic Resonance Imaging – fMRI combined with psychometric measurement scales of trust and distrust, has offered neurological evidence that trust and distrust are associated with different brain areas, and showed their functional distinction at the brain level by means of the identification of distinct neural correlates for their dimensions.

In contrast to trust, distrust has been negatively linked to effective social exchanges, loyalty, communication, cooperative behavior, information sharing, responsiveness keeping promises, and meeting obligations (Dimoka 2010; Gillespie and Dietz 2009; Lewicki et al. 1998). Additionally, the distrust is related to negative emotional feelings such as loss, worry, suspicion, and fear (Dimoka 2010). Distrust can also be defined as an "expectation of injurious action" (Luhmann 2018). In the distrust scenario, the trustee will not act in the trustor's best interests (Barber 1983), reflecting the trustor's expectation about the trustee's poor capabilities, negative motives, and harmful behavior (Ullmann-Margalit 2004). From the perspective of the dimensions, McKnight and Chervany (2001) proposed three analogous dimensions of distrust where the incompetence belief means that trustee does not have the ability or power to do for one what one needs to be done, the malevolence belief is where the trustee does not care about one and is not motivated to act in one's interest, and the dishonesty belief means that the trustee does not make good faith agreements, does not tell the truth and does not keep promises.

Trust and Distrust in Recommendation Agents

Due to the importance of trust to the consumer in e-commerce, RAs are considered trust objects and their use depends on consumer confidence in the RA product recommendations, as well as in the recommendations' inner processes (Gefen et al. 2003; Xiao and Benbasat 2007). Komiak and Benbasat (2006) point out the importance of recommendation familiarity to achieve consumer trust. Gregor and Benbasat (1999) demonstrate that trust in the knowledge-based system can be improved by incorporating transparency. Wang and Benbasat (2016) examined the contribution of preference and requirement explanations (i.e., transparency) in an RA system and demonstrated that it increased users' trust. In the context of RAs, competence belief refers to the consumer's perception that an RA has the skills and expertise to perform effectively in the domains for what it was built, providing the best recommendation, benevolence belief is the consumer's perception that an RA cares about him or her and acts in their best interest, and integrity belief is the perception that an RA adheres to a set of principles including honesty, keeping promises and providing objective advice (Komiak and Benbasat 2006; McKnight and Chervany 2001). On the other hand, the research related to distrust in recommender systems is still in its infancy (Fang et al. 2015; Seckler et al. 2015; Victor et al. 2011). The RA distrust-building process can be defined as an unfavorable interpretation of customer interactions with a recommendation agent that results in a negative expectation that the recommendation agent can be reliable for shopping decisions (Komiak and Benbasat 2008). If a site is not trustworthy enough, customers worry about being harmed, as distrust is strongly bonded to the idea of loss aversion (Dimoka 2010; Kahneman and Tversky 1979; Liu and Goodhue 2012).

Two studies, performed in the USA and Hong Kong, have investigated the differences between a biased RA, with sponsorship disclosure, and a neutral RA (Wang et al. 2018a). The results show that the biased RA lowers users' trust and increases their distrust. However, users' trust in the biased RA could be increased when the RA provides both sponsorship disclosure and explanations. Surprisingly, the effects of lack of recommendation neutrality on distrust cannot be reverted by these explanations (Wang et al. 2018a). The (Seckler et al. 2015) research, with 221 respondents, investigated website characteristics that influence trust and distrust. The study suggests that distrust is related to graphical and structural design issues of a website (e.g., complex layout and pop-ups), beside the privacy issues. Furthermore, the study shows that dishonesty and malevolence are associated with high levels of distrust experience.

Antecedents of Trust and Distrust: Cognitive Effort Perspective

Maximizing accuracy and minimizing cognitive effort are the main objectives of a decision-maker (Wang and Benbasat 2009). According to the effort–accuracy framework proposed by Payne et al. (1993), although consumers have a number of available strategies for making choices, a consumer's decision-making process is often influenced by the trade-off between the perceived quality of the decision and the perceived effort required to make that decision, once more accurate decisions come at the expense of spending more effort. Due to these objectives are often conflicting, trade-offs are necessary between the two (Häubl and Trifts 2000; Hostler et al. 2005; Wang and Benbasat 2009, 2016; Wang and Xu 2018; Xu et al. 2017; Xu et al. 2014a).

The academic literature has produced a series of studies investigating the strategy selection and choice behavior of decision-makers in the context of effort-accuracy when consumers are assisted by decision RAs (Fasolo et al. 2005; Todd and Benbasat 1992, 2000; Wang and Benbasat 2009). For example, Todd and Benbasat (1992) demonstrated that RAs are mainly utilized by users to conserve effort, not necessarily to improve their decision quality. Fasolo et al. (2005) found that features of RAs may lead to better decision quality but also to higher decision effort. The key findings of these studies assert that decision-makers tend to adapt their strategy selection to the type of assistance that maintains a low overall consumption of effort (Xu et al. 2014a). However, when an RA provides support to make a more accurate strategy as easy to employ as a simpler but less precise strategy, then the choice of decision making will be for the implementation of the more accurate strategy. These studies suggest that perceived decision quality and decision effort are the two most important constructs in RA use response (Xu et al. 2014a).

The core functionality of an RA is to apply a decision strategy to integrate users' preferences and then generate product or service advice for them (Wang and Benbasat 2016). The choice strategies employed by the RA to generate product advice also influence decision quality (Wang and Benbasat 2009). The perceived strategy restrictiveness of an RA is related to the competence belief of an RA, by process expectancy of users (Wang and Benbasat 2016). Perceived strategy restrictiveness is defined as decision-makers' perceptions of the extent to which their preferred decision processes are constrained by the functionalities and support provided by a decision aid (Silver 1986; Silver 1988). The concept of system restrictiveness was first proposed by Silver (Silver 1988) and suggests that because the particular predefined decision strategy employed by the RA, this kind of decision support systems restricts users to the decision processes that are embedded in the aid despite the fact that people prefer for a variety of strategies (Silver 1988; Svenson 1979; Wang and Benbasat 2009).

Web-based Transparency Perspective

The information asymmetry between an RA and its users is the most important role of the perceived transparency of an RA in building trust. However, this asymmetry also represents the major obstacle to developing trust in RA because of the agency relationship between the users and the system (Wang and Benbasat 2007). Herlocker et al. (2000) suggest that the low use of RA in high-risk decision-making is due to the lack of transparency. Gunaratne et al. (2018) argue that System designers should accurately represent the source of information to reflect the information provided.

A transparent RA allows users to assess whether the product or service recommendations truly fit their requirements, to verify whether the recommendations are being generated according to its inner workings, to rectify any misattribution related to low integrity belief toward the RA and improve this belief (Wang and Benbasat 2008). Transparency allows users to perform revisions in the input to improve recommendations, avoiding making "shots in the dark" (Sinha and Swearingen 2002). For example, users might be unwilling to commit to a vacation spot without understanding the reasoning behind such a recommendation.

Explanations provide transparency perception, exposing the reasoning and data behind a recommendation (Herlocker et al. 2000), strengthening users' trusting beliefs in the RA's competence and benevolence (Sinha and Swearingen 2002; Wang and Benbasat 2005, 2007) and consequently, increasing the acceptance of an RA (Herlocker et al. 2000). Wang and Benbasat (2007) argued that the explanation facilities of an RA provide factual information and logical arguments, by which users can have a deeper understanding of how the RA generates recommendations, why the RA behaves in a certain way, and how the RA can be used appropriately. As these explanations attempt to convince users with factual information and logical arguments related to their algorithms, they are related to the cognitive-based trust.

Big Data Decision Algorithms effects on Trust and Distrust

Previous studies on persuasion have shown that people faced with a complex decision-making situation usually opt for the effortless peripheral processing rather than the more thoughtful deliberation that involves the central process (Cyr et al. 2018). The main reason is the limitation of computational resources to engage in energy and attention-demanding analytical process. As a consequence, the big data context has encouraged the growth of algorithms, but many remain resistant to using them (Davenport et al. 2010; Dietvorst et al. 2015). Although algorithms have been out performing human judgment in several areas (Alexander et al. 2018), studies point out that people tend to trust more in human experts rather than computerized advice (Alvarado-Valencia and Barrero 2014; Önkal et al. 2009). In fact, despite the algorithms' improved outcomes and their evidence-based focus, people refrain their use them and, lack trust on algorithms until they acquire enough evidence of their reliability (Dietvorst et al. 2015). In other words, as the big data context demands complex algorithms to deal with a condition that demands a high level of cognitive resources, users delay trusting the system until solid and reliable pieces of evidence arise.

In the same vein, the use of big data in the context of recommendation agents is an innovation (Chen et al. 2012; Ul-Ain et al. 2019). Innovation, an idea, practice, or object that is perceived as new by an individual or another unit of adoption (Rogers 2002) is depicted by the innovation theory, which provides a set of innovation attributes that may affect adoption decisions (Rogers, 1995). Among them is relative advantage, which measures the degree that innovation can bring benefits to the users (Papies and Clement 2008; Vijayasarathy 2004) is set to influence the needed trust to adopt a technology.

Although people are able to forgive other people for making the occasional mistake, automated systems are expected to function perfectly every time (Alvarado-Valencia and Barrero 2014). Therefore, when people see an algorithm error, they are less likely to keep using it, even knowing the machine outperforms humans on average (Dietvorst et al. 2015; Gunaratne et al. 2018).

Hypotheses Development

Leveraging the research discussed above, Figure 1 shows the research model for this study. The model aims to test eight different constructs related to the new possibilities brought by the Big Data ecosystem: (1) information completeness, (2) information accuracy, (3) perceived algorithm innovativeness, (4) perceived decision quality, (5) process transparency, and (6) strategy restrictiveness, (7) perceived risk, (8) perceived decision effort.

In this paper, we define information completeness as the extent to which the BDRA provides customers with all of the necessary information or relevant services to accomplish the task (Nelson et al. 2005). Additionally, we posit that the BDRA information accuracy concept encompasses the degree to which users perceive the information provided by the BDRA to be correct and provide accurate recommendations. Since the capability to deliver accurate and complete information reduce the uncertainty and are positively relates to the competence aspect of trust (Venkatesh et al. 2016). We hypothesize:

H1a: Information completeness positively affects the trust belief in a BDRA.
H1b: Information completeness negatively affects the distrust belief in a BDRA.
H2a: Information accuracy positively affects the trust belief in a BDRA.
H2b: Information accuracy negatively affects the distrust belief in a BDRA.

Based on the effort–accuracy framework, users are more likely to adopt an RA if the RA helps increase their decision quality and reduce the cognitive effort expended (Häubl and Trifts 2000; Hostler et al. 2005; Wang and Benbasat 2009). The RAs perform the resource-intensive information processing job of screening, narrowing, and sorting the available options, allowing the consumers to locate and focus on alternatives in an easier manner, and matching their preferences in order to make better quality decisions (Xiao and Benbasat 2007). The use of big data technology allows for decision quality enhancement by means of the addition of reviews, images, ratings, customer behaviors, and social information into the recommendation (Baesens et al. 2016; Chen et al. 2012; Gillon et al. 2014). Thus, the following hypotheses are posited:

H3a: Perceived decision quality positively affects the trust belief in a BDRA.
H3b: Perceived decision quality negatively affects the distrust belief in a BDRA.
H4a: Perceived decision effort in using BDRA negatively affects the trust belief in BDRA.
H4b: Perceived decision effort in using BDRA positively affects the distrust belief in BDRA.

Following prior studies related to strategy restrictiveness (Silver 1988; Wang and Benbasat 2009, 2016), we argue that since a BDRA is capable of processing users' attribute preferences using users' preferred decisions to constrain recommendation options, the strategy restrictiveness might have a negative impact on the trust of users if the processes' user requirements are not how they expect (e.g., an RA with high strategy restrictiveness). In this situation, users will believe the RA is incapable of assisting them in a decision task (Wang and Benbasat 2016). Therefore, we posit:

H5a: Strategy restrictiveness in using BDRA negatively affects the trust belief in BDRA.
H5b: Strategy restrictiveness in using BDRA positively affects the distrust belief in BDRA.

The process transparency is drawn from Wang and Benbasat (2016); Xiao and Benbasat (2007) studies. An RA might be perceived as transparent when users understand the RA's inner workings for producing its recommendations, as well as the RA's underlying motives and characteristics (Wang and Benbasat 2007). The provision of explanations on how the RAs' recommendations reflect users' preferences and requirements will increase users' trust in the RAs (Xiao and Benbasat 2007). Providing additional information increases transparency, which should increase trust (Wang and Benbasat 2007). However, the lack of information may lead to perceptions of complexity and increase the perception of strategy restrictiveness (Wang and Benbasat 2016), which will increase distrust in the BDRA. The big data platform brings more complexity to the RA processing. Therefore, provide information regarding the source of information and de process exerted by de BDRA enhances the perceived transparency in the aid. Thus, we hypothesize that:

H6a: Process transparency positively affects the trust belief in a BDRA.
H6b: Process transparency negatively affects the distrust belief in a BDRA.

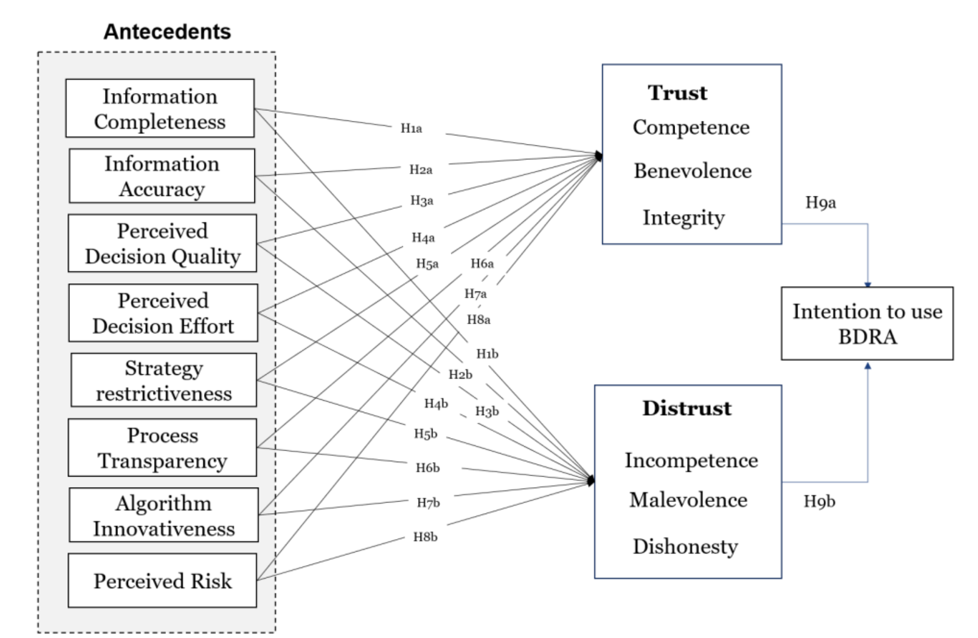

Figure 1. Research Model

Drawing from work on personal innovativeness with information technology (Agarwal and Prasad 1998) and DOI that measures the degree that innovation can bring benefits to the users (Papies and Clement 2008; Vijayasarathy 2004), we define perceived algorithm innovativeness as the degree to which a big data analytics algorithm is perceived as new, different from the heuristics devised by users to support a specific decision. Leveraging PIIT and DOI (Agarwal and Prasad 1998), due to the novel attributes of the big data technology (e.g., variety, velocity, and volume) and the decrease of decision-making complexity we would expect this newness to be positively received. Thus, we hypothesize:

H7a: Perceived algorithm innovativeness positively affects the trust belief in a BDRA.
H7b: Perceived algorithm innovativeness negatively affects the distrust belief in a BDRA.

Perceived risk is the degree of risk users perceive in using a new platform like big data in the recommendation context. Prior studies in RA and trust show that the high uncertainty and risk perception in RA decreases the level of trust in Internet-based systems (Wang and Benbasat 2008, 2016). On the contrary, a high level of perception of risk distrust may increase the distrust associated with the use of RA. We argue that these assertions are also valid to BDRA context. Thus, we hypothesize:

H8a: Perceived risk in using BDRA negatively affects the trust belief in BDRA.
H8b: Perceived risk in using BDRA positively affects the distrust belief in BDRA.

Intention to use is a key dependent variable in the IS field (Brown et al. 2014). Prior research hypothesized that e-commerce trust has a strong relationship with levels of intended use (Gefen et al. 2003). High levels of trust help in reducing the complexity faced by consumers using e-commerce and encouraging online customer business activity. Whereas one of the main objectives of the recommendation systems is also the reduction of the complexity of the decision making by the users, we hypothesize that:

H9a: Trust in the BDRA positively affects the intention to use the BDRA.
H9b: Distrust in the BDRA negatively affects the intention to use the BDRA.

Methodology

We used the Hong et al. (2013) single-context theory contextualization approach that encompass the following steps as guidelines: (1) Grounded in a general theory; (2) Contextualizing and refining general theory; (3) Thorough evaluation of the context to identify context-specific factors; (4) Modeling context-specific factors; (5) Examination of the interplay between the IT artifact and other factors; and (6) Examination of alternative context-specific models.

An experiment was chosen to study our research model. The choice of an experiment was to allow us to exert control over the factors in the study. The experiment assesses the degree of trust and distrust in BDRA in the exchange program selection context. We adopt a 2 (BDRA without transparency, and BDRA with transparency) by 2 (shopping for relative versus shopping for yourself) full factorial model to test the hypotheses. Prior work suggests different salience levels for transparency depending on the purpose of the research (Bettman et al. 1998; Xu et al. 2014a).

We chose to design a BDRA to help participants select an exchange program by simulating the use of big data to gather information from external sources of data before proposing the recommendation. We chose an exchange program due to the ease of including the big data characteristics in the experiment and because exchange program (e.g., study abroad) selection is usually made in a context in which students collect information from many sources like social networks, exchange websites, testimonials, travel agencies, and refer to unstructured information like images and cues from previous users. Additionally, there is an ease in engaging students to participate, since buying an exchange package is something that many students are interested in. After that, we measured trust and distrust beliefs. The experimental BDRA simulated a real operational RA available from leading online decision aid providers with elements of big data (e.g., external sources and social media). A user-aid dialogue elicited users' preferences similar to other studies (Wang and Benbasat 2016; Xu et al. 2014a) and in commercial applications. The BDRA interface encompasses 12 questions related to the attributes: field of study, region destination, credits, course level, previous experience, advice source, program type, destination demand, school ranking, program term, program length, housing. For each of the attributes, nominal or ordinal options (levels) were provided from which users could choose. These attributes and options were drawn from the BDRA available on commercial websites.

Manipulation of Transparency, Shopping Task, and Procedures

The transparency manipulation was performed by building two types of BDRA. The first BDRA provided the source of information used in the algorithm calculation and providing the inner process of the BDRA. The information presented to the respondents was: student social information (Facebook, tweeter, etc.), specialized school site, study abroad providers, public data. Additionally, the BDRA provides the sequence of the information processing that encompassed: (1) identifying and matching external and internal data regarding the respondent preferences, (2) data verification, fraud detection and credit risk, and (3), big data processing, (4) personalized recommendation. After the presentation of the source and processing of BDRA's recommendation, we have shown a summary of all preferences and preferences rating captured.

Different from a traditional laboratory experiment, this study was embedded in an internet survey. As a result, this environment does not have the same degree of supervision that would be experienced in the laboratory. In order to mitigate potential biases, attention checks were included in the experiment and questionnaire. In addition, the manipulation check demonstrates that, although they were not in a lab, the participants were aware of the treatment.

For this study, the participant's task was to select an exchange program abroad. We included two shopping tasks (one for themselves and one for a relative), following prior research that verifies different cognitive and affective behavior between shopping for yourself or for a friend (Bettman et al. 1998; Xu et al. 2014a). During the pilot test, six doctorate students were asked to perform the experiment and give feedback related to the clarity and logic of the task. Figure 2 shows the screenshot of the process for the exchange program presented to the respondents and Figure 3 shows a sample list of recommendations provide by the system.

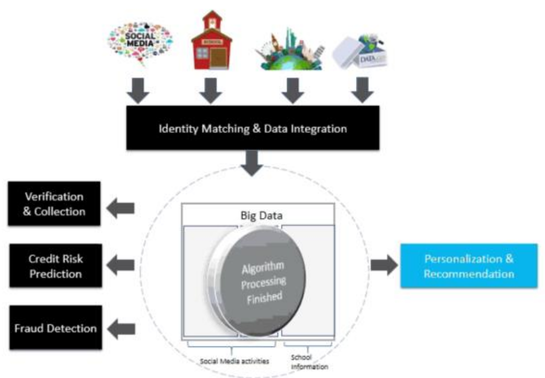

Figure 2. Screenshot BDRA process

Figure 3. BDRA recommendations

Subjects, Incentive, and Procedures

Four hundred students were recruited to participate in the study. An internet link was sent to each of them to grant access to the study. Each student received extra course credit for their participation. We collected 218 valid responses from the students recruited in a public university. The sample used for this study consists of 111 females, 106 males and 1 person that chose not to identify. The group included 3 nonstudents, 52 graduate students, and 163 undergraduates. The age was concentrated in the range of 18-24 year old with 93.1% of the respondents, 5.5 % were in the range of 25 and 35 years old and 1.4 were in the range between 35 and 44 years old. There was no significant difference in gender (Pearson $\chi^2 = 0.33$, $p = 0.95$) or age ($F = 1.57$, $p = 0.22$) distribution across the treatment conditions. The total of 96% of the respondents reported that they have been using the Internet including mobile applications between 2 and 3 years. The data also shows that 3.9% spent more than 24 hours, 51.8% sent between 8 and 24 hours, and 14.2% spent less than 8 hours on the Internet each week. In average, they were slightly familiar with online shopping (1.65 on a five-point scale). When asked about the frequency in use the internet to buy exchange program, 63.3% reported rarely or none use, 22.5% reported to use the internet sometimes, and 14.2% reported to use always the internet to buy an exchange program. Power analysis for a between-subject design determined that 218 subjects would assure a sufficient statistical power of 0.999 to detect a medium effect size ($F = 0.25$) (Cohen 1988).

The respondents were first required to inform their preferences then; they were randomly assigned to the experimental groups (with inner process transparency and without inner process transparency). In the experimental BDRA, they could indicate the product attribute preferences to the BDRA by dragging the slider on each attribute bar (Figure 2). After subjects submitted their attribute preferences to the BDRA, the BDRA accordingly recommended a list of exchange programs that fit students' needs. After that, they answered questions related to the independent and dependent variable of the study. In the end, the respondents were asked to fill in a questionnaire to record their demographic. For the survey instrument, we adopted established scales for trust (Wang and Benbasat 2016), distrust (McKnight and Chervany 2001), from prior literature. The measures use a 7-point Likert scale. The structural model was evaluated using Smart PLS 3.0 (Hair et al. 2016).

Results

Manipulation Checks and Common Method Variance

The manipulation check was conducted to verify that the level of transparency in the experimental BDRAs was sufficient. Analysis of variance (ANOVA) was conducted to check whether the participants perceived the two BDRAs (with process transparency and without process transparency) differently. Significant main effects of the explanations ($F = 4.016$, $p < 0.05$) were found indicating the success of our manipulations.

We conducted the marker variable test (Podsakoff et al. 2003), which is recognized as an effective tool for accounting for common method variance (CMV). A marker variable is believed to be theoretically unrelated to at least one substantive variable, but susceptible to the same causes of CMV. We selected decision self-efficacy as a marker variable. Following Lindell and Whitney (2001), we used the second lowest positive correlation between the marker variable and the six first-order factors as a conservative estimate of shared correlation resulting from CMV. We found that the second lowest positive correlation was 0.079, which was low and nonsignificant. Based on this estimate, we calculated CMV-adjusted correlations using the equation developed by Lindell and Whitney to partial out method variance. The results showed that the differences between the original and the CMV adjusted correlations were very small (from 0.032 to 0.112), suggesting that CMV did not present a major threat to our analysis.

Measurement Model

The model assessment was performed in three steps: (1) internal consistency; (2) convergent validity; and (3) discriminant validity. The study conducted the reliability test to assess the internal consistency of the items by means of Cronbach's alpha and a composite of reliability. The results for internal consistency were satisfactory for all items with values higher than 0.7 (Hair et al. 2013). In addition, all items load well on their respective constructs. The convergent validity of this study obtained values above the value recommended in the literature with AVEs above 0.533 (Hair et al. 2016).

To measure the discriminant validity, two criteria were used: (1) cross loads; (2) the criteria of Fornell and Larcker (1981). The cross loads results for this study shows that no cross loads were found greater than the loadings of the indicators in their respective constructs and the test of Fornell and Larcker (1981) did not find any construct correlations greater than the square root value of the AVE. Table 2 shows the Cronbach's alpha (CA), the composite of reliability (CR), and the Average Variance Extracted (AVE) of the study.

Construct	CA	CR	AVE
Algorithm Innovativeness	0.879	0.943	0.892
Algorithm Transparency	0.911	0.930	0.654
Information Accuracy	0.882	0.927	0.810
Information Completeness	0.918	0.948	0.859
Intention to Use	0.933	0.957	0.882
Perceived Decision Quality	0.825	0.896	0.741
Perceived Risk	0.812	0.914	0.842
Perceived Decision Effort	0.862	0.904	0.707
Strategy Restrictiveness	0.771	0.826	0.633
Trust	0.918	0.931	0.553
Distrust	0.941	0.949	0.610

Table 2. Measurement model assessment

Structural Model

The evaluation of the structural model was conducted by means of the assessments of coefficients of Determination - R^2 and path coefficients. The trust and distrust coefficients are deemed showing strong effects, respectively 60.1% and 50,4% of the variance explanation provided by the independent variables of the study (Cohen 1988). Also, 27.8% of the variance of Intention to use is explained by the model. Table 3 shows the coefficient assessment for trust and distrust antecedents and from them to intention to use.

When analyzing the relationship of trust and distrust with the intention to use, the study shows a significant positive effect of trust beliefs on intention to use ($\beta = 0.516$, $p < 0.001$). The findings, unfortunately, showed that distrust beliefs, in this context, have no significant impact on the intention to use the BDRA. Table 2 shows the results of the structural model assessment.

Hypothesis	Path	Beta	SD	*t*	***pvalue***	
H1a	Information Completeness -> Trust	0.138	0.077	1.780	(ns)	0.075
H2a	Information Accuracy -> Trust	0.308	0.050	6.162	***	<0.01
H3a	Perceived Decision Quality -> Trust	0.354	0.058	6.076	***	0
H4a	Perceived Decision Effort -> Trust	0.063	0.06	1.052	(ns)	0.293
H5a	Strategy Restrictiveness -> Trust	0.053	0.055	0.964	(ns)	0.335
H6a	Process Transparency -> Trust	0.203	0.060	3.442	**	0.001
H7a	Algorithm Innovativeness -> Trust	0.188	0.049	3.862	***	0.000
H8a	Perceived Risk -> Trust	-0.029	0.05	0.582	(ns)	0.560
H9a	Trust -> Intention to Use	0.516	0.053	9.713	***	0
H1b	Information Completeness -> Distrust	-0.095	0.077	1.270	(ns)	0.216
H2b	Information Accuracy -> Distrust	-0.019	0.076	0.255	(ns)	0.799
H3b	Perceived Decision Quality -> Distrust	0.001	0.056	0.021	(ns)	0.983
H4b	Perceived Decision Effort -> Distrust	0.250	0.056	4.498	***	0
H5b	Strategy Restrictiveness -> Distrust	0.157	0.047	3.290	***	0.001
H6b	Process Transparency -> Distrust	-0.154	0.050	3.033	**	0.002
H7b	Algorithm Innovativeness -> Distrust	-0.034	0.057	0.600	(ns)	0.549
H8b	Perceived Risk -> Distrust	0.495	0.054	9.108	***	0
H9b	Distrust -> Intention to Use	0.112	0.065	1.719	(ns)	0.086

Table 3. Structural model assessment

Note: * p < 0.05; ** p<0.01; *** p< 0.001; (ns) = not supported

Discussion

This study investigated trust and distrust as antecedents of use in the context of big data. We draw on trust and distrust literature and identify six antecedent variables related to the big data context: information completeness, information accuracy, perceived decision quality, perceived decision effort, strategy restrictiveness, and perceived risk. Additionally, we incorporate process transparency and algorithm innovativeness constructs to the study, two constructs never tested together before, and very relevant to the context of big data.

The results of the study make important theoretical contributions in four ways. First, a context of decision viewed as much more complex was analyzed. The prior RA studies (e.g., (Häubl and Trifts 2000; Komiak and Benbasat 2006; Wang and Benbasat 2009) only elicited users' product preferences without informing them that a comprehensive process of personal information acquisition would be performed. In the actual environment, when the customers know that companies are gathering information from external sources like social media and other databases, negative perceptions and privacy concerns may arise to stop using the system. We advance the RA literature by proposing to address this tension by comprehensively evaluating the consequences of both trust and distrust.

Second, the study extends the literature about RA trust and distrust presenting two new constructs: process transparency and algorithm innovativeness. The results suggest that users see the algorithm improvement to deal with big data as contributing to the accuracy of the recommendation and consequently increasing the trust beliefs in BDRA. The study results related to process transparency are also significant, suggesting the importance of the big data algorithm understanding for improving trust. Although prior research shows that providing explanations related to the inner workings of a RA increases trust beliefs (Wang and Benbasat 2016), the BDRA brings a new context where the algorithm complexity is not easily understood by users and causing the innovativeness to become relevant. Also, a new finding is the negative influence of process transparency on distrust beliefs, highlighting the importance of explaining the recommendation process to facilitate adoption.

Third, we comprehensively retest prior antecedents of trust in the recommendation agent in the new context of big data. While providing additional support for part of the prior research showing that we must continue considering these foundational constructs, our findings present different results for trust and distrust antecedents, which supports the theorization of McKnight and Choudhury (2006) and Dimoka (2010) that argues that trust and distrust are different constructs and might be manifested simultaneously. The study also adds to Xiao and Benbasat (2007) call for papers that investigate the relationships between decision effort, decision quality and RA transparency with trust.

Fourth, we account for the compounding effects of two IT artifacts, namely big data and recommendation agents by emulating users' online shopping behaviors. This answers the call from the commentary of Brynjolfsson et al. (2010) to study social media systematically rather than in isolation and Chen et al. (2012) by studying trust and issues in the big data context. Additionally, we add knowledge to Big data Literature by means of a behavioral study.

The results regarding the antecedents of trust and distrust in BDRA have practical implications for online companies that have implemented the big data to improve the online recommendations. The study sheds light on important aspects that must be taken into account during the design phase of big data recommendation agents. Developers must take advantage of the perceived innovativeness provided by the new algorithms and by emphasizing the process transparency while nurturing from the power of the big data technology on improving accuracy, decision quality and speed of the recommendations. Knowing how online can be developed and maintained is imperative in an era when organizations increasingly rely on the Internet and social media for influence and recommend their goods and services. Failure on organizations to acquire their clients' trust could significantly prevent users from engaging in online transactions with the organizations. The patterns of trust and distrust processes help to inform BDRA designers about how to build more trustworthy RAs.

Limitations and Future Research

This study has some limitations that represent interesting opportunities for future research. The research was performed by using students as respondents. Although they are an appropriate audience for an exchange program, most of them are not responsible for the final financial decision regarding an exchange program. Future research should evaluate the model in different contexts with different participants. There is also an opportunity to study trust and distrust from the perspective of the organization's decision support systems. These systems are also impacted by the ecosystem generated by big data, representing an opportunity to understand the main aspects related to trust and distrust in an organizational context.

Conclusion

In this study, we conducted an experiment regarding trust and distrust in big data recommendation agents. We used appropriate statistical tests to establish validity, reliability, and perform model testing. In addition, we conducted manipulation tests to assure impacts from the experiment. The study findings identify information accuracy, perceived decision quality, process transparency, and the algorithm innovativeness, as having a positive influence on trust beliefs. Additionally, process transparency, perceived decision effort, the strategy restrictiveness, and perceived risks also have a negative influence on distrust beliefs.

The new ecosystem provided by big data invites us to review our understanding of trust and distrust in order to make the best use of technology and the information now available. These systems have been suffering huge transformations with the new technologies and data available. Therefore, it is important to highlight the aspect that contributes to the trust and consequent use of the systems in this new powerful and challenging context in order to ensure that organizations will be able to optimize their use and capture the benefits of such systems.

Acknowledgement

We want to thank to the Eller College Global Program Department for supporting the data collection phase.

References

Adomavicius, G., Bockstedt, J.C., Curley, S.P., and Jingjing, Z. 2013. "Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects," *Information Systems Research* (24:4), pp. 956-975 (doi: http://dx.doi.org/10.1287/isre.2013.0497).

Adomavicius, G., Bockstedt, J.C., Curley, S.P., and Zhang, J. 2017. "Effects of online recommendations on consumers' willingness to pay," *Information Systems Research* (29:1), pp. 84-102.

Adomavicius, G., and Tuzhilin, A. 2005. "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE Transactions on Knowledge and Data Engineering* (17:6), pp. 734-749.

Agarwal, R., and Prasad, J. 1998. "A conceptual and operational definition of personal innovativeness in the domain of information technology," *Information Systems Research* (9:2), pp. 204-215.

Aggarwal, A. 2016. "A Hybrid Approach to Big Data Systems Development," in *Managing Big Data integration in the public sector*. IGI Global, pp. 20-37.

Alexander, V., Blinder, C., and Zak, P.J. 2018. "Why trust an algorithm? Performance, cognition, and neurophysiology," *Computers in Human Behavior* (89, pp. 279-288.

Alvarado-Valencia, J.A., and Barrero, L.H. 2014. "Reliance, trust and heuristics in judgmental forecasting," *Computers in Human Behavior* (36, pp. 102-113 (doi: https://doi.org/10.1016/j.chb.2014.03.047).

Baesens, B., Bapna, R., Marsden, J.R., Vanthienen, J., and Zhao, J.L. 2016. "Transformational issues of big data and analytics in networked business," *MIS Quarterly* (40:4), pp. 807-818.

Bamberger, P. 2008. "From the editors beyond contextualization: Using context theories to narrow the micro-macro gap in management research." Academy of Management Briarcliff Manor, NY.

Barber, B. 1983. *The logic and limits of trust*. Rutgers University Press New Brunswick, NJ.

Bettman, J.R., Luce, M.F., and Payne, J.W. 1998. "Constructive consumer choice processes," *Journal of Consumer Research* (25:3), pp. 187-217.

Bobadilla, J., Ortega, F., Hernando, A., and Gutiérrez, A. 2013. "Recommender systems survey," *Knowledge-based systems* (46, pp. 109-132.

Brown, S.A., Venkatesh, V., and Goyal, S. 2014. "Expectation Confirmation in Information Systems Research: A Test of Six Competing Models," *MIS Quarterly* (38:3).

Brynjolfsson, E., Hu, Y., and Smith, M.D. 2010. "Research commentary—long tails vs. superstars: The effect of information technology on product variety and sales concentration patterns," *Information Systems Research* (21:4), pp. 736-747.

Chen, H.-M., Kazman, R., and Haziyev, S. 2016. "Strategic Prototyping for Developing Big Data Systems," *IEEE Software* (33:2), pp. 36-43.

Chen, H., Chiang, R.H.L., and Storey, V.C. 2012. "Business Intelligence And Analytics: From Big Data To Big Impact," *MIS Quarterly* (36:4), pp. 1165-1188.

Chen, L., de Gemmis, M., Felfernig, A., Lops, P., Ricci, F., and Semeraro, G. 2013. "Human Decision Making and Recommender Systems," *ACM Transactions on Interactive Intelligent Systems (TiiS)* (3:3), pp. 1-7.

Cofta, P. 2006. "Distrust," *Proceedings of the 8th international conference on Electronic commerce: The new e-commerce: innovations for conquering current barriers, obstacles and limitations to conducting successful business on the internet*: ACM, pp. 250-258.

Cohen, J. 1988. "Statistical power analysis for the behavioral sciences . Hilsdale," *NJ: Lawrence Earlbaum Associates* (2.

Cyr, D., Head, M., Lim, E., and Stibe, A. 2018. "Using the elaboration likelihood model to examine online persuasion through website design," *Information & Management* (55, pp. 807-821 (doi: 10.1016/j.im.2018.03.009).

Davenport, T.H., Harris, J.G., and Morison, R. 2010. *Analytics at work: Smarter decisions, better results*. Harvard Business Press.

Dietvorst, B.J., Simmons, J.P., and Massey, C. 2015. "Algorithm aversion: People erroneously avoid algorithms after seeing them err," *Journal of Experimental Psychology: General* (144:1), p. 114.

Dimoka, A. 2010. "What does the brain tell us about trust and distrust? Evidence from a functional neuroimaging study," *MIS Quarterly* (34:2), pp. 373-A377.

Eirinaki, M., Gao, J., Varlamis, I., and Tserpes, K. 2018. "Recommender systems for large-scale social networks: A review of challenges and solutions." Elsevier.

Fang, H., Guo, G., and Zhang, J. 2015. "Multi-faceted trust and distrust prediction for recommender systems," *Decision Support Systems* (71, pp. 37-47 (doi: 10.1016/j.dss.2015.01.005).

Fasolo, B., McClelland, G.H., and Lange, K.A. 2005. "The Effect of Site Design and Interattribute Correlations on Interactive Web-Based Decisions," *Online Consumer Psychology* (1:1), pp. 304-344.

Fornell, C., and Larcker, D.F. 1981. "Structural equation models with unobservable variables and measurement error: Algebra and statistics," *Journal of marketing research* (1, pp. 382-388.

Fukuyama, F. 1995. *Trust: The social virtues and the creation of prosperity*. Free Press Paperbacks.

Gefen, D., Karahanna, E., and Straub, D.W. 2003. "Trust and Tam in Online Shopping: An Integrated Model," *MIS Quarterly* (27:1), pp. 51-90.

Ghavipour, M., and Meybodi, M.R. 2017. "Trust propagation algorithm based on learning automata for inferring local trust in online social networks," *Knowledge-Based Systems* (143, pp. 307-316.

Gillespie, N., and Dietz, G. 2009. "Trust repair after an organization-level failure," *Academy of Management Review* (34:1), pp. 127-145.

Gillon, K., Aral, S., Ching-Yung, L., Mithas, S., and Zozulia, M. 2014. "Business Analytics: Radical Shift or Incremental Change?," *Communications of the Association for Information Systems* (34, pp. 287-296.

Goes, P.B. 2014. "Big Data and IS Research," *MIS Quarterly* (38:3), pp. iii-viii.

Gregor, S., and Benbasat, I. 1999. "Explanations from intelligent systems: Theoretical foundations and implications for practice," *MIS Quarterly* (23:4), pp. 497-530.

Gunaratne, J., Zalmanson, L., and Nov, O. 2018. "The Persuasive Power of Algorithmic and Crowdsourced Advice," *Journal of Management Information Systems* (35:4), pp. 1092-1120 (doi: 10.1080/07421222.2018.1523534).

Hair, J.F., Black, W.C., Babin, B.J., and Anderson, R.E. 2013. *Multivariate Data Analysis*. Pearson Education Limited.

Hair, J.F., Hult, G.T.M., Ringle, C., and Sarstedt, M. 2016. *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Häubl, G., and Trifts, V. 2000. "Consumer decision making in online shopping environments: The effects of interactive decision aids," *Marketing science* (19:1), pp. 4-21.

Hennig-Thurau, T., Marchand, A., and Marx, P. 2012. "Can automated group recommender systems help consumers make better choices?," *Journal of Marketing* (76:5), pp. 89-109.

Herlocker, J.L., Konstan, J.A., and Riedl, J. 2000. "Explaining collaborative filtering recommendations," *Proceedings of the 2000 ACM conference on Computer supported cooperative work*: ACM, pp. 241-250.

Hong, W., Chan, F.K., Thong, J.Y., Chasalow, L.C., and Dhillon, G. 2013. "A framework and guidelines for context-specific theorizing in information systems research," *Information Systems Research* (25:1), pp. 111-136.

Hostler, R.E., Yoon, V.Y., and Guimaraes, T. 2005. "Assessing the impact of internet agent on end users' performance," *Decision Support Systems* (41:1), pp. 313-323.

Hsiao, R.-L. 2003. "Technology fears: distrust and cultural persistence in electronic marketplace adoption," *The Journal of Strategic Information Systems* (12:3), pp. 169-199.

Jarvenpaa, S.L., Tractinsky, N., and Vitale, M. 2000. "Consumer Trust in an Internet Store," *Information Technology and Management* (1:1-2), pp. 45-71.

Kahneman, D., and Tversky, A. 1979. "Prospect theory: an analysis of decision under risk," *Econometria* (47:2), pp. 263-292.

Komiak, S.Y.X., and Benbasat, I. 2006. "The effects of personalization and familiarity on trust and adoption of recommendation agents," *MIS Quarterly* (30:4), pp. 941-960.

Komiak, S.Y.X., and Benbasat, I. 2008. "A Two-Process View of Trust and Distrust Building in Recommendation Agents: A Process-Tracing Study," *Journal of the Association for Information Systems* (9:12), pp. 727-747.

Komiak, S.Y.X., Weiquan, W., and Benbasat, I. 2005. "Trust Building in Virtual Salespersons Versus in Human Salespersons: Similarities and Differences," *e-Service Journal* (3:3), pp. 49-63.

Lewicki, R.J., McAllister, D.J., and Bies, R.J. 1998. "Trust and distrust: New relationships and realities," *Academy of Management Review* (23:3), pp. 438-458.

Lin, Z., Goh, K.-Y., and Heng, C.-S. 2017. "The Demand Effects Of Product Recommendation Networks: An Empirical Analysis Of Network Diversity And Stability," *MIS Quarterly* (41:2), pp. 397-A310.

Liu, B.Q., and Goodhue, D.L. 2012. "Two Worlds of Trust for Potential E-Commerce Users: Humans as Cognitive Misers," *Information Systems Research* (23:4), pp. 1246-1262 (doi: 10.1287/isre.1120.0424).

Lowry, P.B., Schuetzler, R.M., Giboney, J.S., and Gregory, T.A. 2015. "Is trust always better than distrust? The potential value of distrust in newer virtual teams engaged in short-term decision-making," *Group Decision and Negotiation* (24:4), pp. 723-752.

Luhmann, N. 2018. *Trust and power*. John Wiley & Sons.

Lycett, M. 2013. "'Datafication': making sense of (big) data in a complex world," *European Journal of Information Systems* (22:4), pp. 381-386 (doi: 10.1057/ejis.2013.10).

Malthouse, E.C., and Li, H. 2017. "Opportunities for and pitfalls of using big data in advertising research," *Journal of Advertising* (46:2), pp. 227-235.

McKnight, D.H., and Chervany, N.L. 2001. "Trust and distrust definitions: One bite at a time," in *Trust in Cyber-societies*. Springer, pp. 27-54.

McKnight, D.H., and Choudhury, V. 2006. "Distrust and trust in B2C e-commerce: Do they differ?," *Proceedings of the 8th international conference on Electronic commerce*: ACM, pp. 482-491.

McKnight, D.H., Choudhury, V., and Kacmar, C. 2002. "Developing and Validating Trust Measures for e-Commerce: An Integrative Typology," *Information Systems Research* (13:3), pp. 334-359 (doi: http://dx.doi.org/10.1287/isre.13.3.334.81).

Menon, S., and Sarkar, S. 2016. "Privacy and Big Data: Scalable Approaches to Sanitize Large Transactional Databases for Sharing," *MIS Quarterly* (40:4), pp. 963-982.

Nelson, R.R., Todd, P., and Wixom, B. 2005. "Antecedents of Information and System Quality: An Empirical Examination Within the Context of Data Warehousing," *Journal of Management Information Systems* (21:4), pp. 199-235.

Önkal, D., Goodwin, P., Thomson, M., Gönül, S., and Pollock, A. 2009. "The relative influence of advice from human experts and statistical methods on forecast adjustments," *Journal of Behavioral Decision Making* (22:4), pp. 390-409.

Papies, D., and Clement, M. 2008. "Adoption of new movie distribution services on the Internet," *Journal of media economics* (21:3), pp. 131-157.

Payne, J.W., Bettman, J.R., and Johnson, E.J. 1993. *The Adaptive Decision Maker*. Cambridge: Cambridge University Press.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., and Podsakoff, N.P. 2003. "Common method biases in behavioral research: A critical review of the literature and recommended remedies," *Journal of Applied Psychology* (88:5), pp. 879-903.

Ricci, F., and Werthner, H. 2006. "Introduction to the special issue: recommender systems," *International Journal of Electronic Commerce* (11:2), pp. 5-9.

Rogers, E.M. 2002. "Diffusion of preventive innovations," *Addictive behaviors* (27:6), pp. 989-993.

Seckler, M., Heinz, S., Forde, S., Tuch, A.N., and Opwis, K. 2015. "Trust and distrust on the web: User experiences and website characteristics," *Computers in Human Behavior* (45, pp. 39-50 (doi: 10.1016/j.chb.2014.11.064).

Silver, M.S. 1986. "Differential analysis for computer-based decision support." Graduate School of Arts and Sciences, University of Pennsylvania.

Silver, M.S. 1988. "User Prescriptions of Decision Support System Restrictiveness: An Experiment," *Journal of Management Information Systems* (5:1), pp. 51-65 (doi: 10.1080/07421222.1988.11517816).

Sinha, R., and Swearingen, K. 2002. "The role of transparency in recommender systems," *CHI'02 extended abstracts on Human factors in computing systems*: ACM, pp. 830-831.

Statista. 2018. "Facebook - Statistics & Facts | Statista." from https://www.statista.com/topics/751/facebook/

Svenson, O. 1979. "Process descriptions of decision making," *Organizational behavior and human performance* (23:1), pp. 86-112.

Sztompka, P. 1999. *Trust: A sociological theory*. Cambridge University Press.

Thatcher, J.B., McKnight, D.H., Baker, E.W., Arsal, R.E., and Roberts, N.H. 2011. "The role of trust in postadoption IT exploration: An empirical examination of knowledge management systems," *IEEE Transactions on Engineering Management* (58:1), pp. 56-70.

Todd, P., and Benbasat, I. 1992. "The use of information in decision making: an experimental investigation of the impact of computer-based decision aids," *MIS Quarterly* (16:3), pp. 373-393.

Todd, P., and Benbasat, I. 2000. "Inducing compensatory information processing through decision aids that facilitate effort reduction: an experimental assessment," *Journal of Behavioral Decision Making* (13:1), pp. 91-106 (doi: 10.1002/(sici)1099-0771(200001/03)13:1<91::aid-bdm345>3.0.co;2-a).

Ul-Ain, N., Vaia, G., and DeLone, W. 2019. "Business intelligence system adoption, utilization and success-A systematic literature review," *Proceedings of the 52nd Hawaii International Conference on System Sciences*.

Ullmann-Margalit, E. 2004. *Trust, Distrust, and In Between*. New York, NY:

Vance, A., Elie-Dit-Cosaque, C., and Straub, D.W. 2008. "Examining Trust in Information Technology Artifacts: The Effects of System Quality and Culture," *Journal of Management Information Systems* (24:4), pp. 73-100.

Venkatesh, V., Thong, J.Y.L., Chan, F.K.Y., and Hu, P.J.H. 2016. "Managing Citizens' Uncertainty in E-Government Services: The Mediating and Moderating Roles of Transparency and Trust," *Information Systems Research* (27:1), pp. 87-111 (doi: 10.1287/isre.2015.0612).

Victor, P., Cornelis, C., De Cock, M., and Teredesai, A.M. 2011. "Trust-and distrust-based recommendations for controversial reviews," *IEEE Intelligent Systems* (1, pp. 48-55.

Vijayasarathy, L.R. 2004. "Predicting consumer intentions to use on-line shopping: the case for an augmented technology acceptance model," *Information & management* (41:6), pp. 747-762.

Wang, W., and Benbasat, I. 2005. "Trust in and Adoption of Online Recommendation Agents," *Journal of the Association for Information Systems* (6:3), pp. 72-101.

Wang, W., and Benbasat, I. 2007. "Recommendation Agents for Electronic Commerce: Effects of Explanation Facilities on Trusting Beliefs," *Journal of Management Information Systems* (23:4), pp. 217-246.

Wang, W., and Benbasat, I. 2008. "Attributions of Trust in Decision Support Technologies: A Study of Recommendation Agents for E-Commerce," *Journal of Management Information Systems* (24:4), pp. 249-273.

Wang, W., and Benbasat, I. 2009. "Interactive decision aids for consumer decision making in e-commerce: The influence of perceived strategy restrictiveness," *MIS Quarterly* (33:2), pp. 293-320.

Wang, W., and Benbasat, I. 2016. "Empirical Assessment of Alternative Designs for Enhancing Different Types of Trusting Beliefs in Online Recommendation Agents," *Journal of Management Information Systems* (33:3), pp. 744-775 (doi: 10.1080/07421222.2016.1243949).

Wang, W., Xu, J., and Wang, M. 2018a. "Effects of Recommendation Neutrality and Sponsorship Disclosure on Trust vs. Distrust in Online Recommendation Agents: Moderating Role of Explanations for Organic Recommendations," *Management Science* (64:11), pp. 5198-5219 (doi: 10.1287/mnsc.2017.2906).

Wang, Y., Wang, M., and Xu, W. 2018b. "A sentiment-enhanced hybrid recommender system for movie recommendation: A big data analytics framework," *Wireless Communications and Mobile Computing* (2018.

Wang, Y., and Xu, W. 2018. "Leveraging deep learning with LDA-based text analytics to detect automobile insurance fraud," *Decision Support Systems* (105, pp. 87-95 (doi: 10.1016/j.dss.2017.11.001).

Xiao, B., and Benbasat, I. 2007. "E-commerce product recommendation agents: use, characteristics, and impact," *MIS Quarterly* (31:1), pp. 137-209.

Xu, C. 2019. "A big-data oriented recommendation method based on multi-objective optimization," *Knowledge-Based Systems* (177, pp. 11-21.

Xu, D.J., Benbasat, I., and Cenfetelli, R.T. 2017. "A Two-Stage Model of Generating Product Advice: Proposing and Testing the Complementarity Principle," *Journal of Management Information Systems* (34:3), pp. 826-862 (doi: http://dx.doi.org/10.1080/07421222.2017.1373011).

Xu, J., Benbasat, I., and Cenfetelli, R.T. 2014a. "The nature and consequences of trade-off transparency in the context of recommendation agents," *MIS Quarterly* (38:2), pp. 379-406.

Xu, J.D., Benbasat, I., and Cenfetelli, R.T. 2014b. "The Nature And Consequences of Trade-Off Transparency in the Context of Recommendation Agents," *MIS quarterly* (38:2).

Zhao, J.L., Fan, S., and Hu, D. 2014. "Business challenges and research directions of management analytics in the big data era," *Journal of Management Analytics* (1:3), pp. 169-174.