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Unveiling the Effects of Recommendation Agents on Online Behaviour: An Inquiry Into the Users' Decision-Making Process, Implicit Social Networks and Algorithms Specialization

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To my wife and children. A source of endless love, happiness and motivation. My greatest wealth in this life.

To my mentors. Supportive and constructive counterparts in this path and in the daily challenges. Examples of dedication, patience and love of knowledge.

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Abstract

In the last few decades, the term “algorithm” has become central to the social sciences, albeit its roots are more consolidated and evolved. The origins of the term are indeed dated back to al-Khwārizmī – an ancient Persian mathematician – and to some Euclidean scripts (Striphas, 2015) to refer to a set of mathematical procedures and rules that iteratively transform a group of input in a predefined output (Gillespie, 2014). The profusion of the term and the subsequent application coincide with the development of the Internet and new information technologies (Arnoldi, 2015). Nowadays, this simultaneous processing of users’ information – sent often passively during online activities – is leveraged by companies to direct users to contents/items related to their interests. Importantly, the results of this activity are the videos presented to users on their homepage, the featured posts on social networks, the pop-up advertisements on the visited websites, the appearance order of birthdays of our contacts lists on Facebook and, in general, the majority of things that surrounds our digital existence (Airoldi, 2015).

Specifically, the recommendation agents (RAs), that are central to this dissertation, refer to a particular category of algorithms, which has been implemented on websites with the aim of recommending contents relevant to users and their interests. MovieLens was the precursor of such agents, a platform which automatically processed the opinions of the users (expressed in the form of ratings) to offer contents of interest to the target user (Konstan and Riedl, 2012). Such algorithms change users’ digital experience into a tailor-made path built according to their interests. The growth of e-commerce has led to the exponential implementation of RAs, which, today, are fully integrated in the websites and it is not uncommon to come across the well-known prepositions "you may also like” " or " users who bought this product also bought". The results underlying these prepositions are the result of association rules and mathematical calculations that act as a filter in contexts with enormous assortments (e.g. Amazon.com)(Lash, 2007; Beer, 2009). The main aim of RAs is the reproduction of word-of-mouth that typically occurs between individuals (Ansari, 2000) and, at the same time, they replace the role of "cultural intermediaries" which had the function of disseminating information on new media and / or cultural products (Morris, 2015). However, RAs are not non-evaluative (as might be expected from their mathematical nature), on the contrary they might create a "normalized" culture in which elements beyond the user's interest are excluded (Mackenzie, 2015). Such systems are beneficial for both service

providers and users (Pu et al., 2011). They reduce search costs and facilitate the selection of items in online shopping (Hu et al., 2009) and improve the decision-making and decision quality (Pathak et al., 2010). As a tool for e-commerce, RAs improve revenues, as an effective means of selling more products (Pu et al., 2011).

Although computer science and information technology literature on RAs is extensive, it is still an under-researched topic in the marketing perspective. In the manifold literature on recommender agents, only few relevant contributions have been outlined by marketing scholars with the aim to understand the phenomenon from a consumer and a firm's perspective. Although some topics have been clarified and explained in detail, to date there are still many questions about the effectiveness of RAs.

With the aim to contribute to the extant literature related to RAs, the present thesis collects 3 articles - in 3 chapters - and reflects the evolution of 3 years of investigation on the topic. The findings of Chapter I laid down the foundations for Chapter II and, in turn, the theoretical implications of the Chapter II for the Chapter III.

In Chapter I, I carried out a systematic literature review on the topic, in order to get an organized representation of the phenomenon assuming a 22-year timeframe research period from 2000 to 2022 based on 128 articles. The contributions were then classified according to two theoretical perspectives used by marketing researchers to analyse consumers in RAs-mediated environments, (1) *cognitive psychology* and *(2) social psychology*. Then, the potential similarities among the articles were assessed through a co-citation analysis and multidimensional scaling. I found 26 theoretical frameworks which are recurrently adopted by marketing scholars to conduct research on this topic and refer to three sub fields. The findings contribute to the extant literature by providing an updated understanding of the research on recommender agents.

According to the literature gaps found in the Chapter I, no contributions have been outlined to investigate the implicit social networks enabled by recommendation algorithms, the connection among users inside the network (i.e., neighbours), their role in wide spreading marketing messages and whether dominant users exists in these implicit structures that aim at favouring customization processes.

To this end, in Chapter II, I (1) present a discussion about the role of RAs in the stages of the decision journey and through (2) an analysis of a real-world RAs-enabled network of 37,427 Amazon's users and 1300 products (3) I assess how such agents enable implicit networks of influence inhabited by neighbourhoods of users and (4) the role of consumers in such networks. Therefore, the results emphasize the social nature of RAs-enabled networks and identify most influential users in wide spreading recommendations, according to a set of centrality and community-driven measures. Lastly, some relevant managerial implications are highlighted.

Drawing on such premises, I wondered if implicit influence social networks enabled by RAs really benefit users when associate them to similar ones or not. While prior research has primarily focused on the improvement of accuracy measures as a way to increase the match between users' preferences and recommended items (Song et al., 2019; Dzyabura et al., 2019; Isufi et al., 2021; Hamedani and Kaedi, 2019; Panniello et al., 2014; Zhou et al., 2010; Ansari et al., 2000; Haübl et al., 2000; Knijnenburg et al., 2012; Lombardi et al., 2017; Tsekouras et al., 2020; Aggarwal. 2016), the effects of overspecialization on users' outcomes and their antecedents are currently under-researched. In my idea, higher degrees of RAs accuracy (i.e., the attempt, for some RAs, to match users with similar interests and trigger them with the same recommendations) reduce the information overloading but increase the overspecialization and confines users within their preferences and negatively affect the outcomes of the choice. To respond to this question, in a sequence of four studies reported in Chapter III, 1) I manipulated the RAs specialization level (i.e., overspecialised vs. specialised vs. generalised (Study 1) and degree of novelty of a Recommendation set (RS; novel-based RS vs. accurate RS (Study 4), assessed the perceived reciprocity and intimacy of the RA (Study 2) and the effect on user's expertise (Study 3), but keeping the underlying algorithms unvaried. Study 1 implies three conditions to assess how the increasing levels of RAs learning affects choice outcomes. The results, highlight that higher levels of specialization are associated to lower choice outcomes. Studies 2 and 3 reveal the antecedents of the avoidance of overspecialization. In Study 2, I assess how the RAs learning affects the perceived reciprocity and intimacy of users – as mediators - and in turn the choice outcomes. The results show that users feel a lack of reciprocity and intimacy when RAs increase the knowledge about them. Study 3 investigates how the effects of RAs specialization are detrimental for users due to a reduced chance to form new preferences. The results of this study indicate that RAs are associated to higher choice outcomes when favour the breadth of knowledge rather than the depth. Finally, Study 4 involves an online experiment in which I manipulate two degrees of novelty (high vs. low) and measure their effects on perceived novelty, as a mediator, and choice outcomes. Results show that algorithmic novelty (i.e., the ability of the algorithm to provide items far from users' preferences) is a viable solution to the overspecialization problem and related to higher choice outcomes. The findings contribute to the extant literature (i) by providing an updated understanding of the research on recommender agents and offers insights about the extant research gaps; (ii) emphasizing the nature of RAs-enabled networks, identify most influential users in wide spreading recommendations, according to a set of centrality and community-driven measures, and some relevant managerial implications are highlighted; (iii) measuring the effects of algorithmic overspecialization on users choice outcomes, discover the value of unlearning as a beneficial process to improve product recommendations and shed light on the main antecedents of such issue and discuss the algorithmic novelty as the viable solution.

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Chapter I. "You May Also Like…": A systematic Literature Review on the Effects of Recommendation Agents on User Decision-Making Process

Abstract

Purpose Users can nowadays rely on the support of specific recommendation agents designed to reduce search costs and increase the chance of finding products and services that match their needs and preferences. Typical instances of how recommender agents are placed on e-commerce platforms are represented by statements like "you may also like…" or " People who like this also like " that online buyers typically encounter after having completed a purchase. Although these agents are widely adopted in online shopping contexts, it remains a topic that is largely not researched in the marketing perspective. With the aim to systematise the extant marketing literature on the topic I analysed 128 papers from 59 journals.

Design/methodology/approach The article is based on a systematic literature review on recommender agents in a 22-year research period.

Findings I found that the literature is mainly structured in 3 fields of studies which respectively analyse the RA-related phenomena with 26 different theoretical framework.

Research limitations/implications The paper sheds light on ten under-researched topics which poses the basis for future research.

Practical implications The implications of this paper are relevant to marketing scholars and practitioners who use RAs to strengthen their relationships with their customers. The article suggests a number of directions that the research, publication and reward process could move in to improve practice.

Originality/value Based on the review and the synthesis, I surface researched gaps and provided a ten-point agenda for future research.

Keywords – Recommendation Agents; Artificial Intelligence; Customisation; Literature Review; Consumer Decision-Making Process

Paper type – Literature review

Introduction

One of the key effects of the digital revolution is certainly the increasing complexity and fragmentation of the users' decision-making process (Labrecque et al., 2013). Indeed, while the web offers users a vast array of sources where they can browse to make informed decisions. At the same time, it poses the challenge of elaborating such information in a way that allows users to minimise the risk of making an unsatisfying decision (Hofacker et al., 2016). Nevertheless, users can nowadays rely on the support of specific *recommendation agents* (hereinafter cited as RAs) designed to reduce search costs and increase the chance of finding products and services that match their needs and preferences. Typical instances of how recommender agents are placed on e-commerce platforms are represented by statements like "you may also like…" or " People who like this also like " that online buyers typically encounter after having completed a purchase. Current research has demonstrated that RAs are beneficial for both users and providers (Pu et al., 2011). As regards users, RAs have been shown to improve decision quality and to facilitate the selection of items in online shopping (Hu et al., 2009; Pathak et al., 2010). As for providers, RAs placed on e-commerce sites have been shown to lead to an increase in revenue (Hervas-Drane, 2015; Chen, 2019; Pu et al., 2011). From this perspective, the growing adoption of these algorithms led the International Data Corporation to estimate a global spending in RAs of $5.9 billion in 2019. Such algorithms have extended the concept of Mass customisation posited by Pine (1993), providing personalised product information as well as summarising community opinions and critiques (Schafer, 2007). RAs change the digital experience into a tailor-made experience built on the users preferences, elicited explicitly or implicitly, and thus generate recommendations accordingly (Cheney-Lippold, 2011). The extant literature on RAs provides a twofold perspective. The first is typically referred to in the field of *information technology*, including studies on algorithms design and methods (Herlocker et al. 2004; Liu et al. 2013). A more recent line of research deals with RAs as Decision Support Systems (DSS), a boundary that involves studies on *human-computer interaction* (HCI), *consumer behaviour* and the RAs effectiveness in the marketing process (Zhang and Hurley, 2018a).

Although *computer science* and *information technology* literature on RAs is extensive, it is still an under-researched topic in the marketing perspective. Given the dramatic impact that Ras have on the customer journey I considered it useful to carry out an examination of the current literature on the topic, in order to gain a systematic view of the phenomenon assuming a 22-

year timeframe research period from 2000 to 2022. The papers were then classified according to the main theoretical perspectives used by marketing researchers to analyse consumers in RAs-mediated environments, (1) *cognitive psychology* and *(2) social psychology.* Then, the potential similarities among the articles were assessed through a co-citation analysis and multidimensional scaling. I found 26 theoretical frameworks which are recurrently adopted by marketing scholars to conduct research on this topic and refer to three sub fields. The first section of this paper aims at defining the RAs. Subsequently, the applied methodology is described as the main quantitative and qualitative findings. The findings contribute to the extant literature by providing an updated understanding of the research on recommender agents. Furthermore, the analysis of the investigated variable and theoretical backgrounds offers insights into the main lenses adopted by authors for their studies. Finally, the paper ends with some concluding remarks.

Taxonomy and boundaries

Definitions, methods and dimensions of RAs

Senecal (2004) extended Andreasen's classification of information sources (1968) to computer-mediated environments, asserting that information sources can be categorised into: 1) Personal source that provides personalised information (i.e., "A friend of recommended this product to me"); 2) personal source that provides non-personalized information (i.e., "A well-known expert recommended this product"); 3) impersonal source offering personalised information (i.e., "A RA recommend this product"); 4) Impersonal source that provides non-personalized information (i.e., "Some reports suggest this is the best product available"). In his seminal work, the author argued that recommendation agents are classified as having impersonal information sources which provide consumers with personalised information . Nowadays, according to Xiao et al. (2007) different labels, such as *recommender agents, recommender systems, recommendation systems* have been used interchangeably in the literature to identify the same class of algorithms and information sources. Other scholars suggest that recommender agents are a subcomponent of recommender systems (Meißner et al., 2019). Oftentimes, RAs are improperly associated with reputation *systems* which differ in purpose by collecting, distributing, aggregating and providing feedback about a participants' past behaviour (e.g. eBay rating scale) (Resnick et al., 1997). A further classification was proposed by Spiekermann (2001) who outlined a distinction between RAs adopted in product brokering and merchant brokering. The former refers to algorithms aimed at recommending the best suited product for users, the latter to methods which recommend the best suited vendor (Xiao et al., 2007). In this literature review, I focused on product brokering RAs which are widely adopted on e-commerce platforms, social networks and comparison shopping websites. Furthermore, the recommendation process is mainly based on three stages: 1) when consumers express their preferences for an item, explicitly or implicitly (i.e., *input phase*), 2) the computation of the recommendation (i.e., *process phase)* and the final presentation to the user (i.e., *output phase*) (Xiao and Benbasat, 2007). Ansari et al. (2000) were the first authors who introduced RAs in the *Journal of Marketing*, defining such algorithms as a tool which is able to provide a type of mass customisation. They have outlined two different categories of RAs, namely the *collaborative* and the *content-based filtering*. Collaborative filtering-based RAs suggest products or services by matching customers with similar preferences (Banker et al., 2019), while content-based RAs profile a user's browsing history, along with product features, to find similar products (Choi et al., 2016). The users' preferences are provided through an implicit or explicit elicitation. The former regards the inference of user's preferences during interactions with IT artefacts (Gai, 2019). The latter elicitation process requires extra-effort on the part of the users, asking for an evaluation of the preferred features, categories and items. Evolving from the concept of Mass customisation, other scholars evidence the relevance of RAs in affecting the consumers decision-making process. Häubl et al. (2000) described RAs as tools able to improve the decision quality, reduce the decision making time and decrease the number of alternatives in the consideration set. Farther, Bodapati (2008) in a firm-consumer dialectic, recognises the role of RAs in increasing the chances to sell products with a better match with customers. Kaptein et al. (2018), in his recent contribution, has argued that nowadays firms can rely on a huge availability of data sources to improve the accuracy of the recommendation and the prediction capabilities of RAs. In this vein, in Table 1 the relevant definitions of RAs as well as the proper boundaries of the term are clarified. Although marketing scholars agree on the definitions of RAs, there is still no common consensus on the algorithm methods to be recalled when defining RAs. As regards this purpose, an in-depth analysis of the extant methods and characteristics is provided (see Table 2).

Table 1. Definitions of Recommendation agents

Author(s)	Year	Definition
Aggarwal	2016	Recommender systems utilizes various sources of data to infer customer interests. The entity to which the recommendation is provided is referred to as the user, and the product being recommended is also referred to as an item. Therefore, recommendation analysis is often based on the previous interaction between users and items, because past interests and proclivities are often good indicators of future choices.
Hennig-Thurau et al.	2010	Companies can use such tools for providing highly individualized services and products based on what "similar" customers have enjoyed.
Haϋbl and Trifts	2000	Recommendation agent (RA), allows consumers to more efficiently screen the (potentially very large) set of alternatives available in an online shopping environment. Based on self-explicated information about a consumer's own utility function (attribute importance weights and minimum acceptable attribute levels), the RA generates a personalized list of recommended alternatives.
Senecal and Nantel	2004	[Recommender agents are] impersonal source providing personalized information (e.g., "Based on my profile, the recommender system suggests this product.")
Ansari et al.	2000	Recommendation systems provide a type of mass customization that is becoming increasingly popular on the Internet.[…] Current customization systems fall into two classes that use different information sources to make recommendations. The first class comprises collaborative filtering, which mimics word-of-mouth recommendations. [...] The second class, known as content filtering, makes recommendations on the basis of consumer preferences for product attributes.
Ansari and Mela	2003	Recommendation systems have typically been oriented toward suggesting a new product (e.g., a movie) or service rather than designing Web pages or e-mails.
Bodapati	2008	Recommendation systems that attempt to analyze a customer's purchase history and identify products the customer may buy if the firm were to bring these products to the customer's attention.

A widely accepted taxonomy divided the nature of RAs into two different categories. The basic models, which rely on (1) user-item interactions, such as ratings or buying behaviour, and (2) the attribute information about the users and items such as textual profiles or relevant keywords (Aggarwal, 2016). In domain-specific recommenders, the algorithm takes into account different forms of data, such as time, place-based, and social data. Primarily, the marketing literature has focused on the effectiveness of collaborative filtering, the content-based and hybrid methods of consumers' behaviour. Typical *collaborative filtering* methods are based on the definition of a user-item matrix which describes user's preferences for a set of items. Subsequently, the algorithm matches users with similar tastes and makes recommendations accordingly. The content-based filtering provides advice based on users' past behaviours (i.e., a fan of fiction movies, will get recommendation on recent fiction film that he has not yet watched on the website) (Gai et al., 2019). Hybrid methods involve the combination of different forms of RAs with the purpose to overcome the limitations deriving from pure systems (Aggarwal, 2016; Lim et al., 2021). Although a plethora of methods has been outlined in the *computer science literature*, marketing scholars have mainly focused on basic models. According to the following classification of the accepted definitions of existing methods, the applications and the main authors who cited such approaches have been reported (See Table 2).

Table 2. Recommender Agents methods

Category	**Method(s)**	**Definition**	**Application(s)**	**Author(s)**
Basic Models	Collaborative filtering	Collaborative filtering (CF) is a method based on the computation of a user-item matrix which describes user's preferences for a set of items. Through the definition of the similarity among users profiles, CF matches users with similar interests and preferences. The similarities highlighted contribute to the constitution of a group called *neighborhood*: for which a user will receive recommendations on those items that has never evaluated (in the first person) but which have been positively evaluated by users in his *neighborhood*	Amazon.com	Ansari et al. (2000); Iacobucci et al. (2000); Senecal et al. (2002); Burke (2002); Chakraborty (2002); Aggarwal (2005); Schafer (2007); Montgomery (2009); Pathak (2010); Konstan (2012); Bobadilla (2013); Aggarwal (2016); Thomaz (2020); Srivastava (2020)

Content-based filtering	The recommendations through CBF are based on the preferences stored in the different user profiles. Specifically, evaluations that users have previously expressed on the features of a specific content are compared. Subsequently, the item which reports a high degree of similarity with the preferred features of the user and which have been positively evaluated in the past is recommended.	Netflix.com	Ansari et al. (2000); Kim et al. (2001); Mort (2002); Mattsson (2008); Konstan et al. (2012); Bobadilla et al. (2013); Aggarwal (2016); Virdi et al. (2020)
Knowledge-based	Knowledge-based recommender systems need to employ three types of knowledge; knowledge about the users, knowledge about the items and knowledge about the matching between the item and user's need. In knowledge-based recommendations the user must specify the requirements to allow the system to identify a solution. If no solution can be found, the user must change the elicited requirements. The system can also provide explanations on recommended articles.	FindMe systems	Burke, (2000); Bridge et al., (2005); Wang and Benbasat (2007); Felfernig et al. (2008); Zanker et al., (2010); Aggarwal (2016); Zhao (2018); Khlaus (2020);
Demographic	Demographic-based recommendation systems are based on the calculation of similarities between the demographic information (such as age, sex, profession, etc.) of users. In this approach, the system stores customer demographic information and for each new user on the website the similarity between demographic information with other users is calculated.	Grundy	Qiu and Benbasat (2010); Aggarwal (2016)
Hybrid and Ensemble-Based	Hybrid filtering is a combination of different recommendation methods with the aim of optimizing the system and avoiding some limitations of pure systems. The combination of different algorithms can be done through: 1) separate	Bankruptcy prediction	Kim (2001); Ansari (2018); Gai (2019); Aggarwal (2016); Adomavicius et al., (2012); Stern et

		implementation of algorithms and combination of the results, 2) using a content-based filter in a collaborative approach, 3) using a collaborative filter in a content-based approach or, 4) creating a system of unified recommendations that brings together both approaches.		al., (2009); Schafer (2007)
Domain-specific	Time-Sensitive	Time-sensitive recommenders incorporate temporal knowledge in the recommendation process. The temporal aspect in such recommender systems can be reflected in several ways: 1) the rating of an item might evolve with time, as community attitudes evolve and the interests of users change over time. User interests, likes, dislikes, and fashions inevitably evolve with time; 2) the rating of an item might be dependent on the specific time of day, day of week, month, or season.	News RAs	Liu et al. (2011); Adomavicius et al. (2013); Aggarwal (2016); Zanker et al. (2019);
	Location-based	Location based recommendation has a location aspect built into. A traveling user may wish to determine the closest restaurant based on his previous history of ratings for other restaurants.	Foursquare	Kowatsch et al. (2010); Konstan et al. (2012); Bobadilla et al. (2013); Aggarwal (2016)
	Social	Social recommender systems are based on network structures, social cues and tags, or a combination of these various network aspects.	Facebook	Lombardi et al. (2017); Aggarwal (2016)
	Context-based	Context-based systems take various types of contextual information into account, such as time, location, or social data while making recommendations.. For example, the types of clothes recommended by a retailer might depend both on the season and the location of the customer. Another example is the case in which a particular	Spotify	Aggarwal (2016); Srivastava (2020)

	type of festival or holiday affects the underlying customer activity.	

Furthermore, RAs rely on a set of features that define the overall accuracy and effectiveness of the agent (See Table 3) (Aggarwal, 2005). Specifically, as studied by Konstan et al. (2012), the *relevance* is the ability of an agent to formulate a recommendation aligned to the users' preferences. A higher degree of relevance increases the likelihood to follow the recommendation and the trust toward the agent (Bobadilla et al., 2013). In addition, few studies have focused on the consequences of *novelty* and *diversity* on users' experience. While *novelty* refers to the ability of an agent to recommend new items ("never seen before"),*diversity* regards the variety of items in the recommendation process (Aggarwal, 2016). Some scholars have stated that both dimensions positively affect the likelihood to purchase more products and to increase the sales diversity (Fleder et al., 2009). Prior evidence has also suggested the relevance of *serendipity* in the recommendation process. The term describes the ability of an agent to recommend surprisingly interesting items never discovered before (Zanker et al., 2019). These embedded dimensions pose a solution for the filter bubble issue (Berman et al., 2020). The consumer trust dimension also relies on the interest of marketing scholars. As stated by Xiao et al. (2007), concerns arise deriving from the fact that different types of RAs rely on different degrees of trust. Despite a widespread adoption of the preceding concepts among marketing scholars, the research on *novelty*, *serendipity* and *diversity* varies considerably and it is primarily investigated in *computer science* research.

Table 3. Dimensions of Recommender Agents

Dimension(s)	**Definition**	**Author(s)**
Relevance	The relevance is the primary operational goal of a recommender system which regards the recommendation of items that are relevant and interesting for the user at hand.	Parra et al. (2015); Xiang et al. (2007); Konstan et al. (2012); Aggarwal (2016); Dzyabura and Hauser (2019); De Gemmis et al. (2015)
Novelty	The novelty regards the recommendation of an item that the user has not seen in the past	Aggarwal (2016); Dzyabura and Hauser (2019); De Gemmis et al. (2015)

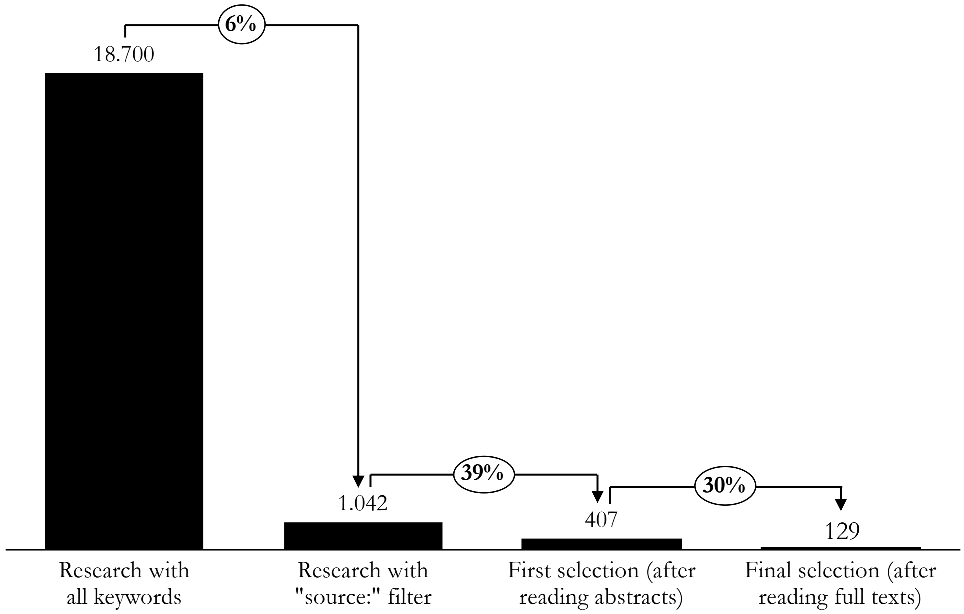
Serendipity	Through the serendipity the items recommended are somewhat unexpected, as opposed to obvious recommendations. Serendipity is different from novelty in that the recommendations are truly surprising to the user, rather than simply something they did not know about before.	Zanker et al. (2019); Aggarwal (2016); Dzyabura and Hauser (2019); De Gemmis et al. (2015)
Diversity	Diversity consists of the capability to recommend different types of items that are not similar among them.	Aggarwal (2016); Dzyabura and Hauser (2019); De Gemmis et al. (2015)
Accuracy	The accuracy refers to the ability of performing recommendations with a high fit with the preferences of the user.	Ansari et al. (2000); Haübl et al. (2003); Knijnenburg et al. (2012); Lombardi et al. (2017); Tsekouras et al. (2020);
Coverage	The coverage regards the ability to recommend a certain proportion of items, or to a certain proportion of the users.	Aggarwal (2016)
Trust	Trust measures the level of faith that the user has in the reported ratings. Even if the predicted ratings are accurate, they are often not useful if the user fails to trust the provided ratings.	Liu et al. (2011); Bobadilla et al. (2013); Aggarwal (2016)
Stability	A recommender system is stable and robust when the recommendations are not significantly affected in the presence of attacks such as fake ratings or when the patterns in the data evolve significantly over time	Bobabadilla et al. (2013); Aggarwal (2016)
Scalability	Ability of a recommender systems to perform effectively and efficiently in the presence of large amounts of data.	Aggarwal (2016)

Research on consumers' response in RAs-mediated environments involves different theoretical perspectives. Xiao et al. (2007) found several frameworks through which past literature analysed the behavioural outcomes in RA-dominated contexts and the users' evaluations of RAs. The present study enlarges the extant literature toward a more complex and articulated picture of 26 theoretical frameworks adopted by scholars to explain the effects of RAs on the consumer decision-making process. Frameworks adopted in order to observe the contributions of scholars, along a time span of 22 years, are traced back to two branches of psychology, namely *cognitive psychology* and *social psychology*. With regards to *cognitive* *psychology*, scholars based their studies on the following theories: (1) *theory of reasoned action,* (2) *trust theories* (3) *theory of planned behaviour* (4) *technology acceptance model,* (5) *unified theory of acceptance and use of technology*, as well as the following new theories (6) *algorithm acceptance model, (7) information processing theory*, (8) *cost-benefit theory*, (9) *search-theory, (10) mental accounting theory, (11) prospect theory* and *(12) expectation disconfirmation theory.*, In addition, through the lenses of *social psychology*, researchers outlined several contributions based on *(13)theelaboration likelihood model, (14) media equation theory, (15) construal level theory*, (16) the *similarity-attraction theory,* (17) *Hofstede's cultural model,* (18) *Schwartz's theory of basic human values,* (19) *Social comparison theory,* (20) *assemblage theory,* (21) *gender theory, (22) complexity theory, (23) configurational theory, (24) gift-giving theory, (25) uses and gratification theory and (26) social presence theory.* Accordingly, I examined 128 articles from 59 journals deriving from three main components in the existing literature of RAs.

Methodology

Considering the main purpose of this paper was to review the extant marketing literature on the topic of recommender agents with the aim to fill potential gaps, the research was conducted focusing on three types of journals: (1) Marketing; (2) Economic, business and management and (3) Human-computer studies. The analysis started with the definition of a query for searching only relevant documents through the Web of Science. Authors carried out an extensive search using the keywords "*recommender system*", "*recommendation agents*", "*recommender agents*", "*online recommendation system*", "*online recommender system*", "*online recommendation agents*" in the title, abstract and full texts. The observed timespan goes toward a 22-year research period from 2000 to 2022. Using the "exact phrase" keywords without narrowing the sources, 18.700 documents were reported. In this perspective, the second step involved a delimitation of sources. Authors recalled only journals in the field of marketing, consumer behaviour and management. This step led to 1042 papers, out of which 407 were selected after reading the titles and abstracts. Subsequently, after a first reading of the full texts, about 300 papers were excluded because they were considered incompatible/ inconsistent with the study purposes. As a result, I finally selected 128 articles from 59 journals. Figure 1 summarises the stages of the article identification process.

Figure 1. Selection process



The articles were then analysed in terms of: (1) Publication year; (2) Names and number of authors; (3) The underlined theoretical framework;(4) The type of study; (5) The analysis carried out; (6) The investigated variables and associated keywords.

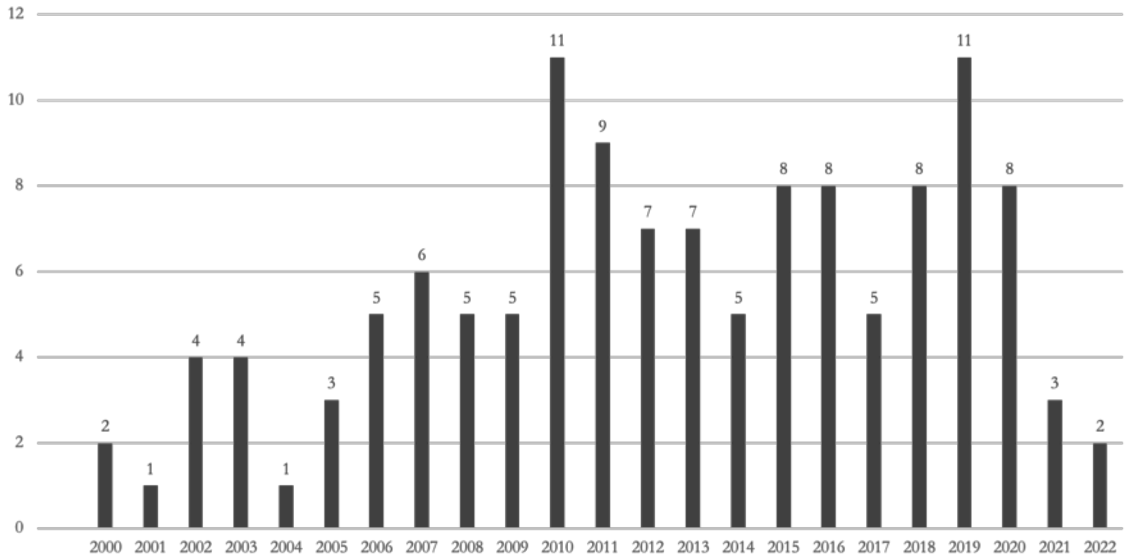
Subsequently, a co-citation and multidimensional scaling technique analysis was adopted to assess the degree of correlation among the studies and the underlying structure.

Results and discussions

Quantitative findings

The 128 papers analysed were collected from 59 journals (Table 5). Since the timeframe goes from 2000 to 2022, an increasing focus on the topic over the years has been noticed with two peaks of interest in 2010 and 2019.

Figure 2. Publication(s) per year



Of the above mentioned papers, 85 were empirical studies, 23 research papers, 2 books and 13 literature reviews (see Figure 3).

Figure 3. Classification of articles/books

Across the empirical studies, several methodologies have been adopted. As shown in Figure 4, the most used methodologies are ANOVA (21 times), Factor analysis (13 times), Correlation analysis (11 times), Mediation analysis (10 times) and MANOVA (9 times). Only few authors adopted mixed (Wang et al., 2008) and qualitative methods (Dabholkar et al., 2012; Virdi et al, 2020) to conduct their studies. 260 variables have been investigated according to *cognitive* and *social psychology* theories (Appendix A and Appendix B)). As for *cognitive psychology*, I found that scholars based their studies on (1) *theory of reasoned action,* (2) *trust theories* (3) *theory of planned behaviour* (4) *technology acceptance model,* (5) *unified theory of acceptance and use of technology*, and the new (6) *algorithm acceptance model, (7) information processing theory*, (8)*cost-benefit theory*, (9)the *search-theory, (10) mental accounting theory, (11) prospect theory* and *(12) expectation disconfirmation theory*. Through the lense of *social psychology*, researchers outlined several contributions based on *(13) elaboration likelihood model, (14) media equation theory, (15) construal level theory*, (16) *similarity-attraction theory,* (17) *Hofstede's cultural model,* (18) *Schwartz's* *theory of basic human values,* (19) *Social comparison theory,* (20) *assemblage theory,* (21) *gender theory, (22) complexity theory, (23) configurational theory, (24) gift-giving theory, (25) uses and gratification theory* and (26) *social presence theory.* As shown in Appendix B, the most used theoretical frameworks are the *information-processing theory, technology acceptance model* and *media equation theory.* Also, the analysis involves 318 authors and approximately 2,58 contributors per article.

The most cited article is *Hybrid recommender systems: Survey and experiments* written by Burke et al. (2002), followed by Ricci et al. (2011) and Koufaris et al. (2002) (see Table 4).

The most prolific journals on the topic are the *International Journal of Human Computer Studies, Journal of Management Information Systems, Journal of Interactive Marketing* and *Journal of Marketing Research* (see Table 5). Authors also carried out a co-citation analysis to further explore whether there exists relevant association among authors. and the results are visually represented in Table 6.

Table 4. Relevant authors and number of citations

Authors	**Times cited**	**Times cited/Year**
Burke et al.(2002)	1583	79.15
Ricci et al.(2011)	1518	138.00
Koufaris et al.(2002)	1270	63.50
Senecal et al.(2004)	635	35.28
Corritore et al.(2003)	493	25.95
Komiak et al.(2006)	492	30.75
Xiao et al.(2007)	377	25.13
Park et al.(2012)	267	26.70
Vance et al.(2008)	245	17.50
Konstan et al.(2012)	239	23.90

Table 5. List of journals

Journal	**#**
International Journal of Human Computer Studies	15
Journal of Management Information Systems	12
Journal of Interactive Marketing	9
Journal of Marketing Research	8
International Journal of Information Management	6
Journal of Consumer Psychology	5
Journal of Marketing	4

User Modeling and User-Adapted Interaction; Journal of the Academy of Marketing Science; Journal of Retailing and Consumer Services; Journal of Services Marketing	3
Journal of Marketing Management; International Journal of Human-Computer Interaction; Journal of Consumer Behaviour; European Journal of Marketing; Information Systems Research; Journal of Consumer Research; Marketing Science; Computers in Human Behavior; Journal of International Consumer Marketing	2
Springer; International Journal of Retail and Distribution Management; International Journal of Retail & Distribution Management; International Journal of Human-Computer Studies; Mis Quarterly; Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior; Journal of Research in Interactive Marketing; Journal of Database Marketing & Customer Strategy Management; Journal of Service Management Research; Journal of Digital Information Management; Knowledge-Based Systems; Journal of Global Scholars of Marketing Science; MIT Sloan Management Review; International Journal of Hospitality Management; Information and Management; International Journal of Information Science and Management; Journal of Retailing; Expert Systems with Applications; Journal of Service Management; Journal of Management and Marketing Research; Journal of Service Science and Management; International Journal of Internet Marketing and Advertising; Direct Marketing: An international Journal; International Journal of Management & Information Systems (IJMIS); Journal of Consumer Marketing; Journal of Marketing Analytics; MIS Quarterly: Management Information Systems; International Journal of Marketing Studies; Recommender Systems Handbook; International Journal of Research in Marketing; The Adaptive Web; Journal of Marketing Theory and Practice; Journal of Public Policy and Marketing; Journal of International Technology & Information Management; International Journal of Advertising; Journal of Business Research; International Journal of Electronic Commerce; Journal of Computer Information Systems; Information & Management	1

Figure 4. Top Authors' production over time

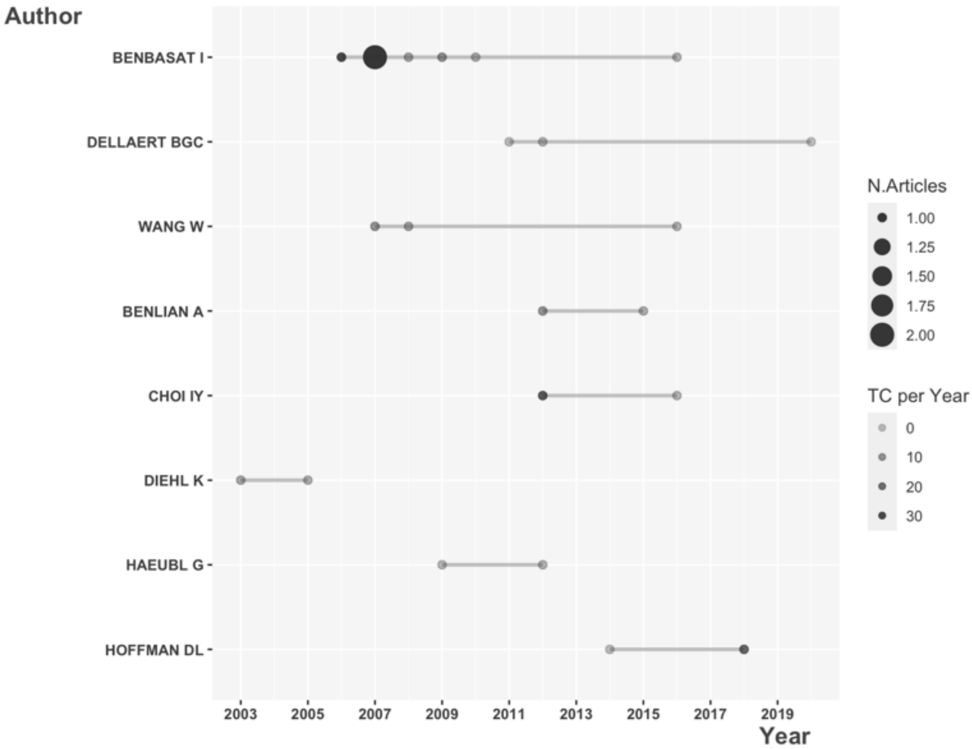
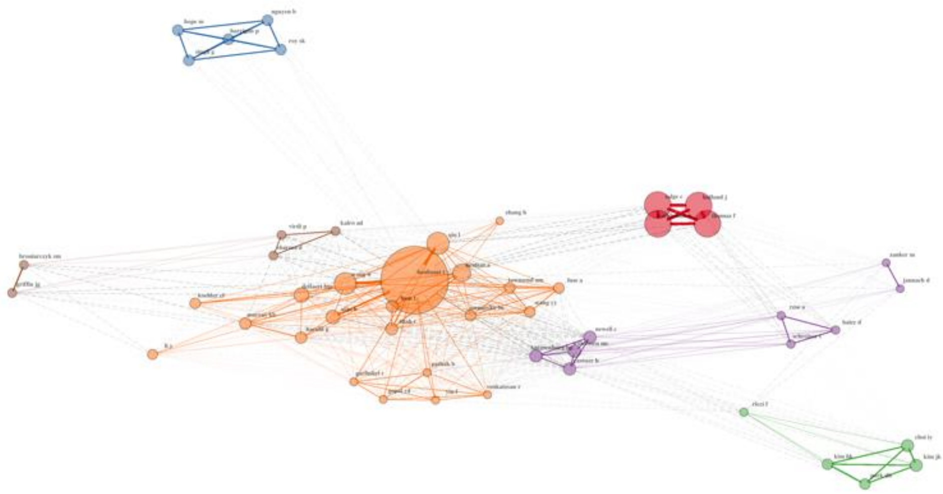


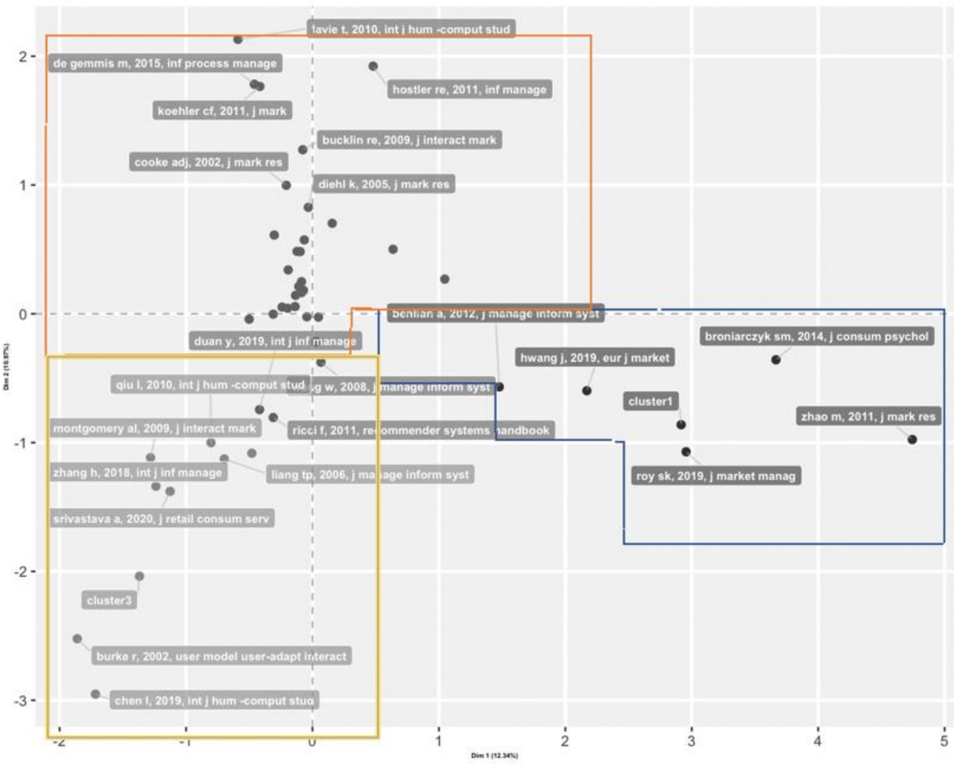
Figure 5. Co-citation networks



Qualitative findings and multidimensional scaling

One of the main purposes of this study was to outline a broader framework through which to orientate the reading of the extant literature of RAs. Authors identified three main approaches deriving from a factor analysis which studied the relationship between each author and defined a structure among the articles. Namely, an *information processing-oriented* field in which authors assessed message processing and relevant cues associated with RAs. A second *acceptance – oriented* approach aims at evaluating the intention to accept an algorithmic recommendation provided by an RA and a *relationship-oriented* approach which investigates the effects of social cues on behavioural intentions.

Figure 6. Multidimensional scaling



Cluster 1: RAs acceptance oriented field
Cluster 2: Information processing oriented field
Cluster 3: Relationship-oriented field

Information processing - oriented field

According to the literature of *information processing*, Haübl et al. (2003) posited that providing a list of attributes in RAs as an explanation to support consumers' choice, recommendations are more effective. They also put forward that both the inclusion of an attribute and an effective presentation format increases the processability of the advice (Haübl et al., 2003). Although the RAs improve the decision quality and decrease decision making time and the effects of the significant interaction have been explained in the process. Swaminathan (2003) explained that the amount of searching in a RAs-mediated environment, is moderated by product complexity, category risk and consumer category knowledge (i.e. *expertise*)., In addition, RAs reduce the number of evaluated product alternatives, while including a full-set of attributes., At the same time, in high category risk-recommendation agent conditions, consumers are more likely to choose nondominated alternatives (Swaminathan, 2003, Eslami et al., 2022). However, the latter research does not support significant evidence for the moderating role of category knowledge. Aggarwal (2005) found that RAs improve the decision quality and decision-making time during the shopping of search goods, while in the case of experience goods, results are considered comparable to those obtained in absence of RAs. Evidence also supported by Yan et al. (2016), has demonstrated that users are more likely to accept personalised recommendation in a hedonic product dominated context . Furthermore, when consumers are forming a consideration set, RAs should present more alternatives and leverage, and more on the *novelty* of the recommendations (Yan et al., 2016). In his seminal work, Gai et al. (2019) the relevance of using user-based filtering instead of item-based filtering was outlined. Framing the same recommendation with a user-based filtering, which emphasises the similarity between customers, increases the click-through *rate,* while cueing respondents to their dissimilarities with other users and increasing the acceptance of an item-based filtering (Gai et al., 2019). Similar evidence has been pointed out by Punj (2007), who has confirmed the differences among "smart agents' ' and "knowledgeable agents' ' in affecting consumers' responses. The former refers to an agent informed with the alternatives by the user. The latter provides the same capabilities of a knowledgeable agent but including the capability to suggest alternatives that nearly fit in with the selection criteria. When a "smart agent" is used, less searching is conducted and more alternatives are evaluated. While the reverse is true using a knowledgeable agent (Punj, 2007). With the *prospect theory* lense, Adomavičius (2013) discussed evidence of biased output effects on the consumers' preference ratings. Priming an online shopper with the ratings of other users, lead to conceiving the recommendation as a suggestion to a "correct" answer. In turn, users tend to adapt their evaluation to those expressed by others (Adomavičius, 2013). Drawing from the *search-theor*y, Delleart et al. (2012) found that RAs induce considerations in line with a predefined set of alternatives. Thus, when consumers inspect a new product provided by a recommendation they tend to make comparisons with previously encountered alternatives (Delleart et al., 2012). In particular, RAs cause consumers to rely less on newly inspected products and to attribute more utility to the best previously encountered alternatives (Delleart et al., 2012). Aforementioned studies explain the relevance of RAs in reducing search costs, while generating a greater product selection, and sorting alternatives on behalf of the consumer (Diehl, 2005; Alba et al., 1997). All the preceding beneficial dimensions are also discussed by Diehl (2005) who demonstrated that in the ordering mechanism for screening the environment on the basis of consumers' preferences, lower-ranked alternatives offer a relatively small chance of exposing consumers to better options, increasing the search efforts and the information overload. Furthermore, using RAs to screen and sort product alternatives negatively affects price sensitivity (Diehl, 2002; Koo, 2015). The process of sorting different alternatives seems to increase the weight of quality relating to price in consumers' choice, in a twofold manner. First, producing an ordered list of prospective products tends to create an oversampling effect on more attractive options (Diehl, 2005). Second, due to the high similarity among these options, consumers focus more on price-related attributes. Moreover, presenting the set of recommendations in a descending list sorted by quality, leads consumers to an increasing focus on product quality, while figuring out the recommendation with an ascending list will increase the relevance of the price (Cai et al., 2008). Goodman et al. (2013), also investigated the influence of recommendation signages on the consideration sets. Authors have outlined that signs can hinder choice for consumers with developed preferences, increasing the difficulty and complexity in taking a decision . Signages create conflicts leading to an augmented consideration set for those with developed preferences, while positively affecting consumers who are going to develop their own preferences (Goodman et al., 2013, Wuang et. al, 2010). Based on the *mental accounting theory,* Punj (2011) states that high-income shoppers are affected by time-saving features to a greater extent than lower-income users. Similarly, high-educated consumers prefer environments that offer products that match their needs. Among these groups, neither seems focused on the money saving aspects (Punj, 2011). The abovementioned findings were further investigated by White et al. (2014). The authors found that consumers keep balanced mental accounts for contingent or temporally integrated exchanges when faced with the prospect of disclosing personal information to receive incentives (White et al., 2014). Yet, when the benefits precede costs, as in the case of a non-contingent exchange, consumers keep separate mental accounts in which they devalue the marketers' incentives which make them less likely to reciprocate by disclosing information. When the benefits precede the costs, the former are less salient due to the temporal distance and lead to reduced outcomes for online marketers. From a managerial perspective, marketers benefit from understanding the consumers' willingness to give and to reciprocate favours. For instance, when a consumer reports a high attitude to reciprocate, the perceived benefit could be heightened through an explicit requirement of cost (e.g., consumers will pay a price premium for the recommended services)(White et al., 2014). Through the *cost-benefit theory*, Kim (2020) has confirmed the discussed evidence experimenting the effects of the perceived benefits of information search, demonstrating that greater is the perceived benefits of the information search, greater will the attitudes toward RAs and the perceived value of RAs be.

RAs Acceptance-oriented field

As a suitable theoretical foundation for explaining the adoption of new technologies, TAM has been used by several researchers to investigate attitude and behavioural intentions toward the RAs. Cho et al. (2015) reported that customised recommenders positively affect the perceived usefulness and ease of use. Senecal et al. (2004) focused on the analysis of the RAs characteristics in order to investigate the effects of the likelihood to accept the recommendations for RAs. Researchers have demonstrated that RAs have a greater influence than human experts for choosing experience products. These circumstances augment the intention to follow the recommendation and their perceived usefulness. However, the same results are not supported in the case of search products (Senecal et al., 2004). Similarly, the attitude towards RAs is negatively affected by commercial aspects of personalisation, poor quality and exceeding recommendations (Odou et al. 2011; Joerß et al., 2021). Furthermore, the acceptance of RAs is also affected by the attitudes toward the web site. Koufaris (2011) for example extended the TAM by introducing the shopping enjoyment in the model as well as a variable affected by perceived value of search mechanisms, web skills and tasks. He has described the online consumers in a twofold perspective: as a shopper and as a computer user. The author found that the presence of search mechanisms in a website influences the online experience and the enjoyment of the user which in turn influences the behaviour and the intention to return to the website. In contrast, integrating the consumer participation in the model, the perceived ease of use of the RA is negatively affected by consumer interaction with the RA, while it is also positively correlated to the enjoyment of using the RA (Sheng et al., 2014). In addition, Benlian et al. (2012) extended the framework assuming the effect of the *RA type*, the *product type*, *RA use*, *trusting beliefs* and the *perceived affective quality of the RA* on the *intention to purchase based on the RA* and *intention to reuse the RA*. They found that not all recommendations equally influence trusting beliefs, perceived affective quality, and perceived usefulness. Consumer reviews exert a greater influence on trusting and affective beliefs rather than on RAs. The latter have stronger effects on instrumental consumer beliefs. Also, highly perceived usefulness is the main driver for intent to reuse the RA (Benlian et al., 2012). Furthermore, groups of consumers are more likely to accept an algorithmic group recommendation when social relationship quality is high (Hennig-Thurau et al., 2012). The aforementioned findings are supported by the evidence of Baier et al. (2010), who confirmed the effect of the perceived usefulness of the intention to use the RA, but explaining the variable as a consequence of two declared antecedents: the output quality and the shopping relevance. Thus, recommended products that match with users' preferences (i.e. *output quality*) and recommendations that make shopping more simple or convenient (i.e. *shopping relevance*) are positively correlated to the perceived usefulness (Baier et al., 2010). Additionally, the RA characteristics such as autonomy (i.e. the RA executes instructions according to its own perception and does not rely on users instructions), reactivity (i.e. the RA understands the results that are generated after executing actions and can perform the most appropriate corresponding actions) and learning ability (i.e. through the items it perceives and the user's search records enhance its own ability and knowledge by monitoring and learning) exert an influence on the behavioural intentions. All these effects are mediated by the perceived risk (i.e. *time risk, privacy risk and performance)* (Chao et al., 2016). Supporting this evidence, other researchers demonstrated that including privacy features on personalisation tools increases the behavioural intention toward the website (JungKook, 2010). The acceptance of RAs toward the TAM framework has also been investigated for in-store shopping behaviour. Adopting RAs in in-store shopping environments, the behavioural intention is strongly predicted by the perceived usefulness which in turn predicts the intention to prefer a retail store and the intention to buy. Alternatively Chen et al. (2017), argued that an extension of the TAM proposed by Davis (1989) is needed to investigate the algorithm acceptance. Shin et al. (2020) proposed an *Algorithm Acceptance Model* (AAM) based on the TAM, demonstrating the occurrence of heuristic and systematic processing when perceiving algorithm effectiveness. Authors verified that the usage and interactions of an algorithm are positively related to perceived values, which are related to user processing of transparency and accuracy as well as to future intention. Besides, algorithmic features and interactions are positively connected to trust. Perceived features of the algorithm certainly affect the trust toward the RA, which in turn increases the sense of customisation, security and accuracy. Despite the increasing attention to the *technology acceptance models,* several researchers draw their theoretical foundation from the *theory of reasoned action* (TRA) and *theory of planned behaviour* (TPB). In a seminal work, Komiak et al. (2006) used the TRA to build a research model which describes the causal chain from perceived personalisation and familiarity (perceptions) to specific use intentions (trusting intentions). The investigated behaviour referred to the RAs use. Consistent with the TRAs, authors postulated the positive association of trust in competence and cognitive trust in integrity along with emotional trust. Also, the cognitive trust in competence and integrity affects the behavioural intention toward the RA and are more important than the competence belief. While the latter has a higher effect on the willingness to adopt the RA than integrity. It implies, in order to enhance the UX, the provision of explanations able to clarify the underlying logic of the RAs (Komiak et al., 2006). Drawing on the TRA, Knijnenburg et al. (2012) demonstrated that behavioural intentions are affected by some experience variables, such as viewing time and the number of viewed products and relationships decrease the browsing but not the consumption. Consistent with the literature, Smith et al. (2005) describes that trusting beliefs are explained by the expertise declared by the RAs and the similarity between the agent and the consumer. The above mentioned variables are also moderated by the shopping goals (i.e. hedonic vs. utilitarian) (Smith et al., 2005). As for the *theory of planned behaviour*, many authors have investigated the effects of the perceived control on behavioural intention. According to Dabholkar et al. (2012), the consumer participation in using RAs (i.e. the perceived control exerted on the agent) positively affects the trust toward the RAs, the recommendation and the website. In turn, those trusting beliefs predict the willingness to reuse RA, the website and to buy according to RA recommendations (Dabholkar et al., 2012). Wang et al. (2007) posits that to facilitate the formation of consumers' trusting beliefs, marketers should focus on the *agency relationship*, epitomised as the necessity of signalling (i.e. to provide assets and designs that are clearly visible and signal high quality) and *incentives*. The agency increases the perceived control which enables subsequent trusting beliefs. Researchers pointed out that explanations on *how* the recommendation has been figured out and on *why* the RAs suggested a product, increases the trust propensity toward the RAs. Other results confirmed that customers who believe their preferences are stable and are more likely to accept customised recommendations. In contrast, those who believe they have less stable preferences, tend to reject customised recommendations. In turn, perceived customisation enhances the accuracy evaluation and receptiveness for those with high preference stability (Shen et al., 2011). Hostler et al. (2011), by analysing the effects of the usage of RAs on impulse buying behaviour, shen demonstrated the relevance of user satisfaction in affecting the unplanned purchase. As antecedents, customer satisfaction in an RA-mediated environment is predicted by the product promotion effectiveness (i.e. a product that fits with the users' expectations and needs) and the effectiveness of the product search. Thus, greater the RA accuracy is, greater is the declared user satisfaction. As a consequence, this causal chain also explains the variables affecting the likelihood of unplanned purchases. According to the authors, user satisfaction increases the likelihood of unplanned purchases (Hostler et al., 2011). Using the lens of expectations-disconfirmation theory, Shen (2014) poses that the main sources of dissatisfaction rely on the typology of algorithm (e.g. ITunes algorithm could be preferred to a collaborative filtering based on the wisdom of the crowd), poor convincing connections (e.g. a misleading connection between the recommended product/service and the viewed ones), ceiled discovery (e.g. the algorithm always recommends the same products), the sales motive exerted by the merchant, poor customer knowledge, attitudes towards privacy and inaccuracies of the recommendation (Shen, 2014). Zhang et al. (2018b) proposed an innovative theoretical framework which connects design features to the consumers' perceived personalisation and trust. They found that the RAs' explanations about the underlying logic of recommendation, positively affects the trust and the intention to accept it. They found that the consumers' trusting belief in the RA's competence and integrity is affected by different forms of explanations (textual vs. graphical) and is mediated by the consumer's perceived customisation of the RA. Furthermore, Corritore et al. (2003) confirmed the model proposed by Zhang et al. (2018b) stating that the trust in RAs is increased by a conversational interface and disclosure of what the RA is aware of. Other authors proposed a materialisation of trust by computing a recommendation method able to derive the degree of trust thanks to the documents' ratings of the user. The method includes the computation of time factors and document similarity. Time factors allow to offer recommendations close to the current time and increase the trust toward the advice. Finally, the aforementioned models are often embedded into common collaborative-filtering method to effectively discover trustworthy neighbours for making recommendations (Liu et al., 2011). The results showed that the prediction accuracy of recommendation is improved and trust increases when both factors are combined and incorporated (Liu et al., 2011).

Relationship-oriented field

Among the studies which focused on *social psychology*, Ansari et al. (2000) were the first authors to introduce the RAs in the marketing literature, explaining their role of mimicking the word-of-mouth recommendations which take place in human-to-human interactions. Considering RAs as social actors, they described the relevance of the wisdom of the crowd as nurturing for these agents. Moreover, authors went into great detail to explain the underlying mechanisms of collaborative filtering as systems needing dense user preference-related data frames to accurately predict the recommendation. Extant literature outlines a deeper analysis of the interaction of human-objects which conceptualises the *assemblage theory* as a determinant framework so as to explain such experiences. Hoffman et al. (2018) recognized the dimensions of agency, autonomy and authority in intelligent agents. The agency refers to interaction skills of the agents, that is having the ability to affect and to be affected (Hoffman et al., 2018). They are autonomous in the extent to which they act independently with or without humans, while the authority deals with the intelligent agents' control on responses to users or other entities and on how others respond to them (Hoffman et al., 2018). The above mentioned capabilities, allow to conceptualise an object experience that emerges from the interactions of the object and can be classified along two dimensions: 1) the ability of the object to enable and constrain the whole, 2) the ability of the whole to enable and constrain the object and 3) their ability to play an agentic or communal role (Hoffman et al., 2018). According to Pathak et al. (2010), word-of-mouth enhanced RAs are also beneficial for merchants decreasing the consumers' price sensitivity, allowing to increase their price as a counter-effect of providing more information about the product, and customising recommendations. Drawing on these assumptions, Iacobucci et al. (2000) have investigated the optimal mechanisms to compute the similarity among users. They found that marketers, based on their priorities, should recommend products which respond to the highest similarity score between consumers, between viewed products and consumers*viewed products. It might seem tautological but considering the nature of RAs, several recommendations are provided only according to the similarity of the items (i.e. content-based filtering) and similarities among consumers (i.e. collaborative filtering). Including these three dimensions in the process of recommendation will increase the effectiveness of the RAs and the tie among similar consumers (Iacobucci et al., 2000). Continuing on the *similarity-attraction theory,* Choi et al. (2016) overcome the RAs underlying process of implicit elicitation of preferences, such as the click-through data, proposing a model which includes the users' facial expression during the consumption or fruition of an item. They found that this approach strongly outperforms other systems when recommending items to the neighbourhood. Lombardi et al. (2017) draw from the *social-comparison theory* to build RAs based on the preferences of people within the users' social

network. Authors outlined that the proposed RA overperforms compared to other traditional agents, and consumers found the recommendation more complete and informative. Furthermore, Walter et al. (2015) analysed the perceived social presence of non-human-agents. They argued that overall the human-agents exert a greater influence on the users' intention to adopt the recommendation. While richer feedback media is able to convey more social cues, it also increases the perception of social presence. It means including a video or an audio in the RAs, outputs a higher level of social presence in individual reports (Walter et al., 2015).
An emerging field of marketing research has shown that social cues can exert an influence on behavioural intentions, satisfaction and user experience (Köhler et al., 2011). Most of them draw on the media equation theory which suggests that individuals tend to treat media (or, as in this case, online agents) as humans when employing social cues (Reeves et al.,1996). The authors proposed that online agents, such as RAs, with intelligent memory and interaction capabilities can serve as effective socialisation agents. They argued that online agents involve customers in interactive conversations and can apply past interaction content to current interactions (Köhler et al., 2011). Providing customers with functional content about a service (i.e. a recommendation based on the characteristics) increases the perceptions of self-efficacy, the feeling of being accepted by the organisation and the perceived ability to use the firm's services (Köhler et al., 2011). Adopting social content for newcomers makes consumers dissatisfied, while such content is important to build a friendly relationship with the RA. Furthermore, a proactive interactive style has a moderating role on newcomers. It suggests that RAs should be designed to initiate and maintain customer interactions (Köhler et al., 2011; Murray et al., 2009)). Humanoid embodiments and output modalities also enhance social interactions between RAs and their users (Qiu et al., 2008) RAs with a human face increase the social presence than disembodied RAs. Additionally, RAs with a human voice induce greater social responses from users than text-based RAs. Also, it has been found that ethnicity-matched RAs are perceived as more enjoyable, useful and socially present (Qiu et al., 2010). Subsequently, gender-matched RAs do not exert a significant influence on consumers. Hanus et al. (2015) posits that the customisation of an RA through an avatar leads to higher brand liking and to greater purchase intention. Customising an avatar increases the intrinsic motivation and feeling of autonomy, competence and enjoyment and this then leads to an increase in brand liking and purchase intention (Hanus et al., 2015). Similarly, considering RAs as social actors implies the increase of the reciprocity in human-agent interactions. Lee et al. (2017) stated that self-disclosure opens up a channel for reciprocal exchange and interaction,

they found that increasing the self-disclosure of an RA leads to a more satisfactory experience. Besides, reciprocity significantly predicts relationship building between human and agent along with user satisfaction. An agent that can reciprocate makes the interaction more believable and realistic (Lee et al., 2017). Imbuing technological sources with the specialisation cues (i.e. Wine agents, Shoes agents, etc.) lead to a greater perceived expertise of the RAs which also increases the trust toward the RAs and improves the decision making time (Koh et al., 2010). As in human-to-human interactions, different forms of reasons (i.e. Dispositional, Institutional, Heuristic, Calculative Interactive, Knowledge-based) predict the trust in RAs (Wang et al., 2008). Drawing on the *attribution theory*, Wang et al. (2016) and Vance (2008) studied the three components of trusting beliefs: competence, integrity, and benevolence that are widely acknowledged in trust literature. They observed that the cognitive effort, advice quality, and perceived strategy restrictiveness (i.e. performance factors) affect the competence belief whereas the perceived transparency of an RA (i.e. knowledge-based reason) influences competence, integrity and benevolence. As for the *complexity theory and configuration theory*, other authors outlined how different configurations of the RA can affect the purchase intention (Komiak et al., 2006; Lee et al., 2009, Tsekouras et al., 2022). Lee et al. (2009) demonstrated that in the presence of RAs with anthropomorphic characteristics, the gender affects the trust toward the RA. For instance, they showed that consumers, when associated to an algorithm, considered the gender as a psychological and not biological. As a result, they tended to evaluate the RA beyond any stereotype on the gender and increase their trust toward the recommendation. Furthermore, some scholars found that as in human-to-human interactions, the users' culture also influences the human-agent interactions. Srivastava et al. (2020) tried to manage grey sheep users (or *outliers*) using the foundations of *Schwartz's theory of basic human values*. They predicted the likelihood to be an outlier evaluating the score reported for Schwartz's values. The study found that the enjoyment of consumers and their sense of community is affected by the culture. Similarly, past research proved that collectivist cultures tend to build new relationship using social networks or to help others (Kim et al. 2021). This finding is also empirically supported by Png et al. (2001), who observed that individuals residing in countries dominated by low uncertainty always seek for new technologies. Through Hofstede's cultural value of uncertainty avoidance, the researchers postulated that cultures provided with a high degree of uncertainty avoidance tend to place less trust in IT artefacts than individuals from low uncertainty avoidance cultures. In addition, such cultures pose less relative importance to web site design and characteristics (Vance et al, 2008)

Extant literature oftentimes analyses the persuasion exerted by RAs under the lens of the Elaboration Likelihood Model (Cacioppo et al., 1984). I found 5 papers out of 128 which adopted this theoretical framework. Examining the persuasive power of different sources in the context of the savings systems, Gunaratne et al. (2018) posit that both the presence of an algorithmic advice and crowdsourced advice increases the likelihood of achieving a saving goal in comparison to a condition where a recommendation is not provided. Furthermore, the above mentioned researchers stated that facing an account holder with an algorithmic calculation is more persuasive than a recommendation promoted by peers. In such cases, subjects rely on the *authority* of the algorithmic source rather than on *social proof*, using the peripheral route for processing the recommendation. Besides, a series of experiments showed that the likelihood of accepting a customised recommendation is greater when consumers are able to identify measurement methods adopted to calculate their preferences. This evidence has been observed only for individuals with low expertise and by removing the declaration of stated preferences decreases the likelihood of following the recommendation, prompting respondents toward more transparent tasks (Kramer, 2007). Consistent with the extant literature, Liang et al. (2006) posit that declaring the methods through which preferences have been elicited and calculated is not the only relevant dimension for influencing the processing of a recommendation. Indeed, the author found that the individual motivation positively affects the perception of the RAs accuracy, and greater the motivation greater the perceived accuracy (Liang et al., 2006). Moreover, analysing the argument as the primary determinant of influence, Wang et al. (2010) built on the Toulmin's model of argumentation and the ELM explained the likelihood of accepting a recommendation, considering the presence of a spokesperson in the message. Authors found that including a spokesperson in the recommendation as opposed to not including one did not lead to higher perceived argumentative quality. While, priming the subjects with the statement "spokesperson recommends this item" promoted by an RA, increases the source credibility (Wang et al., 2010).

According to the construal level theory (CLT), 4 papers out of 128 have investigated the influence of RAs on the consumers' decision-making process. In his seminal work, Lambrecht et al. (2013) demonstrated that by putting subjects in an abstract or concrete mindset using a generic retargeting (i.e. a brand-level ad) versus dynamic retargeting, the latter, in general, is not significantly effective. They argued that generic ads are more influential than dynamic retargeted ads. Therefore, authors explored whether the consumers' intention to accept the RAs recommendation changes after seeing other consumers' reviews. After visiting a website of reviews, consumers tend to respond in a positive manner to a dynamic ad (Lambrecht et al., 2013). In other research, authors draw from the literature on psychological distance to explore how recommendations influence users' preferences as an effect of the incongruence between temporal and social distance (Zhao et al., 2011). They posit that recommendations are more persuasive when consumers decide for the distant future. Since they take place at a high level, the mental construct related to other people's opinions is congruent with that of distant-future decisions. Also, they have demonstrated that the time-contingent effect of recommendation on preference shift is attenuated when the recommendation is made for a natural product which is strongly preferred (Zhao et al., 2011 Time affects decision making according to the consumer's future orientation and the response time of the RA. In regards to the social distances, Zhao e t al. (2011) found that being close to others affects near-future preferences, while recommendations from distant-others are more effective in changing distant-future preferences. They demonstrated that the congruency between the RAs output and consumers' mental representation (concrete vs. abstract) increase the likelihood to accept the recommendation (Zhao et al, 2011).

Hwang et al. (2019), focusing on the contextual factors of spontaneous *gift giving*, with an emphasis on the effect of the recipients' valence outcomes on the givers' motivation and behaviour, explained the empathy gap in terms of the givers' emotional difference caused by changes in state self- esteem as a result of comparisons with the recipients' circumstances. Authors found that the empathy gap affects gift-giving behaviour with regard to the effort exerted in the selection. Gift givers too went on to consider the recipient's perspective more when recipients experienced a misfortune. Additionally, the empathy varies according to the valence of git occasion. Empathetic reaction differs depending on the valence of events experienced by others, and that asymmetric empathy leads to differences in gift-giving behaviour. They applied these findings to RAs arguing that marketers should recommend gifts according to the occasion (i.e. such as congratulations, retirement, graduation, etc.). Also, considering that valence of others' outcomes affect the gift motivation and gift choice, marketers should incorporate this factor in RAs to help consumers with low emotional commitment and relatively short time as well as effort involved in building consideration sets and in providing appropriate messages for the occasion. At the same time, when the giver has a great commitment, marketers can promote personalised items and unique gifts that can convey greater empathy for the giver.

Conclusion

Brief summary

The present article aimed at developing a systemic literature review of recommender agents and identify under-researched area and gaps. The most recent review dates back to 2007, leading to the need of an updated version. In the literature review, the main definitions, methods and characteristics adopted by other authors have been investigated and analysed to provide a further systematisation of extant research. The research in this field is mainly empirical and focuses on 26 theoretical perspectives. The findings advance the existing knowledge on RAs and offer a recent depiction of the research. The identification of the 26 theoretical frameworks is a further step toward understanding the main perspective of the analysis that has been adopted in each existing contribution, as it underlines what has been done so far and what may be still lacking. Furthermore, the analysis of the investigated variables gives interesting insights into how these approaches relate to each other in terms of similarities and differences.

A Ten-Point agenda for new research avenues

In the manifold literature on recommender agents, few relevant contributions have been outlined by marketing scholars posing the foundations to understanding the phenomena from a consumer's perspective as well as a firm's perspective. Although some topics have been clarified and explained in detail, to date there are still many questions about the effectiveness of RAs. The in-depth review of the literature has led me to highlight 10 gaps as foundations for future research. [1] According to the current literature, marketing scholars only focus on a few recommendation methods. However, there are no detailed contributions in terms of acceptance of *demographic*, *context-based*, *time-sensitive*, *location-based* and *social* RAs. Furthermore, the accepted definitions of RAs in the literature are oftentimes limited to 3 methods, which are *collaborative filtering*, *content-based filtering* and *hybrid and ensemble filtering*. [2] A second line of research proposed for the future, concerns the analysis of the entire set of RA characteristics. Although there is a significant focus on the *relevance*, *accuracy*, *trust* and *coverage* characteristics, little is still known in relation to the effect of the *novelty*, *serendipity* and *diversity* of RAs. [3] Moreover, in the plethora of theoretical perspectives, a fully accepted model for explaining the acceptance of algorithmic recommendations is not yet evident. Even if until now a primordial contribution has been outlined through the *algorithmic acceptance model*, the latter still needs further investigation considering all the cognitive, social and cultural dimensions which are involved in human-agent interactions. Subsequently, among the aforementioned theoretical frameworks referring to *cognitive and social psychology*, there are very few contributions, with the exception of Gai and Klesse (2019) relating to the effects on marketing metrics (such as, *CTR*, *Impression* , *Conversion rate*, etc.). [4] Besides, the relevance of these agents is always described in relation to the purchasing phase. No specific outcomes were identified for the other phases of the consumer decision journey and what influence these recommendation agents exerted accordingly. Specifically, how can they build awareness and stimulate consumer engagement as well as assist users in the post-purchase phase (e.g. by recommending products related to past purchases)? How can different forms of explanations (or methods) be adopted to increase cognitive proximity? [5] As regards to this point, although the social and cultural aspects have been partially investigated, there is even so a lack of contributions on the methods of presenting the explanations. Current contributions focus on *construal level theory*, *Hofstede's cultural model* ,*Schwartz's theory*, or on the *similarity-effect.* With the aim of increasing human-agent cognitive proximity, no studies have been outlined to explain the process of customisation of RAs based on the explanation methods (*e.g.* language) to be automatically adapted in relation to each user, on the basis of social and cultural specifications. [6] Also, USI noticed that contributions related to different rewarding methods for users based on a recommendation process are yet missing. From a human-algorithm interaction perspective, it would be interesting to investigate which forms of implicit or explicit rewarding can be implemented to improve the effectiveness of these agents. [7] Moreover, in line with the study advanced by Hoffman and Novak (2018), I noticed that currently there are no studies that can explain the relationships that are established between algorithms placed at the service of the user and the user himself. This finding could also be linked to the next one, in relation to the analysis methods to be adopted. [8] However, it has been noticed that the presence of qualitative or mixed studies is restricted when related to the plethora of empirical studies based on quantitative methodologies. It suggests further investigation methods for the future. [9] An additional point concerns the possible differences that may exist in relation to specific categories of users. as there are no clear distinctions in relation to consumer type. Although there are contributions related to hedonic and functional consumption or to consumers with different levels of expertise, there are no findings in relation to different age groups, levels of income, impulse-buying consumption, consumers with different social and status needs. [10] Finally, as a last point, no contributions are made in relation to recommendations based on spatial or temporal proximity.

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Appendix A. Theoretical framework(s) and investigated variables

Theoretical framework	Variable(s)
Algorithm acceptance model	*Perceived Transparency; Perceived Fairness; Trust; Perceived Usefulness; Perceived Convenience; Intention to adopt; Perceived personalization; Perceived accuracy*
Assemblage theory	*Agency; Authority; Autonomy*
Attribution theory	*Advice quality; Perceived effort; Trust; Perceived Transparency; Perceived strategy*
Complexity theory; configuration theory	*Trust; Perceived privacy; Emotional response*
Construal level theory	*Distance-future preference; Near-future preference; Perceived relevance; Time-contigent effect; RS type (concrete vs. abstract); Perceived transparency; Intention to accept the recommendation; Type of retargeting; Type of recommendation; Perceived uselfulness; Cognitive complexity; Adoption intention*
Cost-benefit theory	*Perceived costs; Perceived benefits; Attitude toward the RA; Perceived value of RAs; Intention to use*
Elaboration Likelihood Model	*Advice type; Intention to follow the recommendation; Argument; Perceived Quality; Source credibility; Argument Form; Spokeperson Type; Perceived Expertise; Perceived Ease of use; Task transparency; Preference understanding; Trusting beliefs; Trusting intention; Browsing behavior; Purchasing behavior; Involvement*
Expectations disconfirmation theory	*Customer satisfaction; Satisfaction; Perceived Price; Accuracy; Perceived Similarity; Perceived Value; Perceived quality; Satisfaction; Product promotion effectiveness; Product search effectiveness; Unplanned purchase; RA use; Perceived cognitive effort; Perceived cognitive fit; Satisfaction; Product Alternatives; Time available; Number of Search Iterations; Explanation type*
Gender theory	*Gender; Trusting beliefs; Trusting intentions*
Gift-giving theory	*Valence; Esteem; Empathy; Gift-selection efforts*
Hofstede's cultural model	*Perceived Enjoyment; Sense of community; Social Commerce acceptance*
Information processing	*Attractiveness; Processing Time; Product Set granularity; Decision quality; Decision time; Attribute importance; Choice styles; RA use; CTR; User-base framing; Item-based framing; Dissimilarity cues; Focal attractiveness; Search effort; Price; Number of product selected; Accuracy; Perceived quality; Satisfaction; Intention to follow the recommendation; Perceived risk; Product complexity; Category knowledge; Product category risks; Expertise; Type of consumption (public vs. private); Social risk; Financial risk; Performance risk; Product type; Number of characteristics recommended; Recommendation context; Unfamiliar recommendation; Recommendation similarity; Recommendation timing; Product portofolio; Product attributes; Recommendation effects; Risk taking; Decisional guidance(Conservative vs. Aggressive); Credibility indicators(Low vs. High); Switching behavior; Confidence; Consumer expertise; Perceived expertise; Task complexity; Tradeoff difficulty;Preference uncertainty; Consumer empowerment factors; Freedom of choice; Expanded information possibilities; Decision difficulty; Timing, Selected alternatives; Vividness; Self reference; Product screening cost; Product evaluation cost; Website characteristics; Customer loyalty; Type of explanations; Weighted additive utility; Relative utility;Attribute sum; Dominant alternatives; Attribute difference; Non dominated; Fit; Liking Interest; Super functionality; Perceivied personalization; Smart-experience co-creation;Perceived cognitive effort; Perceived cognitive fit;Product Alternatives; Time available;Number of Search Iterations;Perceived costs; Perceived benefits; Attitude toward the*

	RA; Perceived value of Ras; Intention to use; Decision quality; Decision difficulty; Assortment size; Sign conflict; Preference development; Low search costs; Number of recommended products; Decision quality; Number of product alternatives evaluated; Product attractiveness; Product choice; Perceived utility; Perceived utility; Sales increase; Price; Quality; Assortment Size
Media Equation Theory	*Agency; Intrinsic motivation; Brand liking;Perceived humanness; Cognitive experiential state; Affective experiential state; Trust; Intention to use premium service; Perceived value of personalization; Ease to use; Antropomorphic dimension; Social acceptance; Self-efficacy; Role clarity; Style type; Content type; Financial outcomes;Computer type;Trust toward computer;Trust toward website;Trust toward web agent; Decision time; Perceived intimacy; Perceived trust;Perceived interactional enjoyment; User satisfaction; Self disclosure; Intention to use; Gender; Ethnicity; Social presence; Perceived Enjoyment; Perceived uselfulness; Social presence; Human embodiment (avatar vs. none); Output modality (voice vs. text); Trusting beliefs; Perceived usefulness; Perceived enjoyment; Usage intentions; Type of source*
Mental accounting theory	*Cognitive ability; Perceiveid net disclosure; Trusting beliefs; Perceived utility; Time; Expenditure; Enjoyment*
Prospect theory	*Perceived quality; Product sorting method; Anchoring(low vs.high)*
Schwartz's theory of basic human values;	*Users' traits; Accuracy*
Search-theory	*Decision quality; Decision difficulty; Assortment size; Sign conflict; Preference development; Low search costs; Number of recommended products; Decision quality; Number of product alternatives evaluated; Product attractiveness; Product choice; Perceived utility; Perceived utility; Sales increase; Price; Quality; Assortment Size*
Similarity attraction theory	*Gender; Ethnicity; Social presence; Perceived Enjoyment; Perceived uselfulness; Accuracy; Similarity; Gender; Voice type; Face type; Time*
Social Comparison Theory	*Perceived utility*
Social presence theory	*Type of feedback; Perceived social presence;perceived feedback usefulness;perceived trustworthiness;Perceived enjoyment will; Type of source*
Technology acceptance model	*Transparency; Fairness; Trust; Usefulness; Convenience; Intention to adopt; Perceived personalization; Perceived accuracy; Perceived ease of use; Perceived uselfulness; Intention to use the RA; Intention to prefer RA-enabled retail store; Perceived Enjoyment; Perceived uselfulness; Attitude toward personalization; Attitude toward the website;Consumer Participation in Using an RA;Financial Risk Involved in a Purchase;Perceived Ease of Use of the RA; Enjoyment; Perceived uselfulness; Intention to use; perceived affective quality; perceived usefulness; perceived ease of use; provider recommendations; trusting belief; product type; Intention to purchase; Intention to reuse RA; Perceived playfulness; Price perception; Convenience perception; Perceived product quality; Perceived desire to shop without a salesperson; Perceived product information; Purchase Intention; Product involvement; Intention to return; Unplanned purchase; Attitude toward using; Behavioral intention; Output quality; Shopping relevance; Time risk; Privacy*

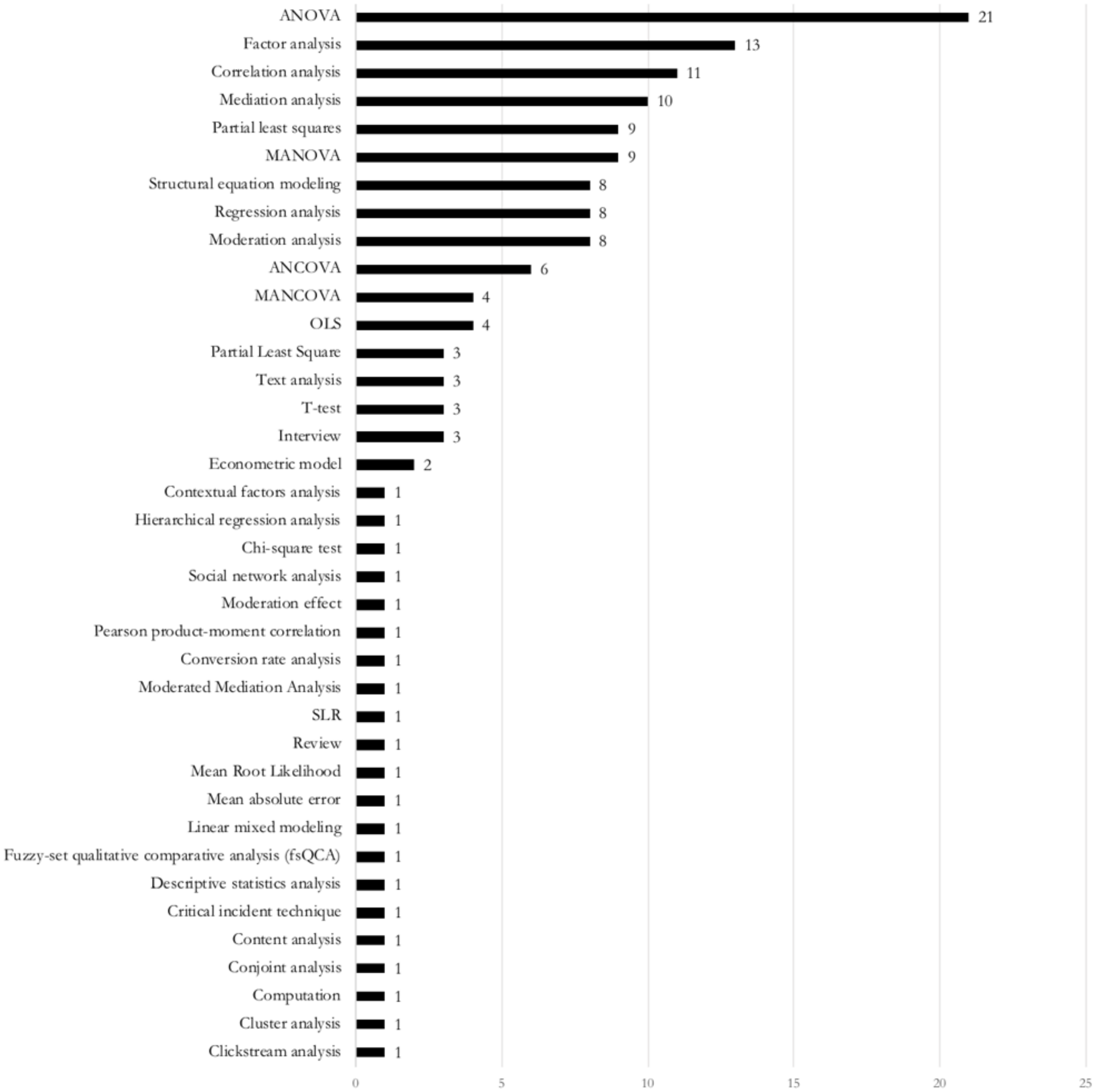
	Risk; Performance; IA Autoomy; IA Reactivity; IA Learning; Privacy concern features; Personalization features; Website type; Recommendation type; Social presence; Perceived value
Theory of planned behavior	*Perceived control;Privacy concerns;Perceived recommendation quality;Customization mode; Privacy intrusion; User engagement; Controllability; Expertise; Familiarity; Trusting propensity; Trust toward RAs; Trust toward site; Intention to reuse RA; Intention to purchase; Trusting belief; Type of explanation; Ease-of-use; Preference stability belief; Accuracy evaluation*
Theory of Reasoned action	*Perceived personalization; Familiarity; Intention to adopt as a decision aid; Intention to adopt as a delegated agent; Agent perceived credibility; Agent perceived reliability; Agents' efficacy; Institution-based trust; Ease of use; Trusting beliefs; System quality; Web site quality; Culture; Interest; Perceived recommendation quality; Perceived Trust; Expertise; Shopping goals; Perceived influence of recommender; Product choice; Credibility; Trusting beliefs; Trusting intention; Browsing behavior; Purchasing behavior; Involvement*
Trust	*Explanation Availability;Explanation Mode; Perceived personalization; Trust - Integrity; Trust-Competence; Intention to adopt; Cognitive trust in competence; Cognitive trust in integrity; Emotional trust; Dispositional Reason; Institutional Reason; Heuristic Reason; Calculative Reason; Interactive Reason; Knowledge-based Reason; Trust in RA;Trust toward computer;Trust toward website;Trust toward web agent; Trust; Accuracy; Trust toward RAs; Trust toward site; Intention to reuse RA; Intention to purchase; Trusting belief; Type of explanation ;*
Uses and Gratification	*Customer satisfaction; Accuracy; Satisfaction*
Unified theory of acceptance and use of technology	*Perceived ease of use; Perceived uselfulness; Perceived playfulness; Cross-buying intention; Impulse purchase intention; Relevant cues*

Appendix B. Theoretical framework(s) and investigated variables

Theoretical framework	**No of. Papers**
Information processing	*22*
Technology acceptance model	*15*
Media Equation Theory	*10*
Expectations disconfirmation theory	*6*
Search-theory	*6*
Theory of planned behavior	*6*
Theory of Reasoned action	*6*
Similarity attraction theory	*5*
Construal level theory	*4*

Elaboration Likelihood Model	*4*
Trust	*4*
Mental accounting theory	*3*
Prospect theory	*2*
Social presence theory	*2*
Uses and Gratification	*2*
Algorithm acceptance model	*1*
Assemblage theory	*1*
Attribution theory	*1*
Complexity theory; configuration theory	*1*
Cost-benefit theory	*1*
Gender theory	*1*
Gift-giving theory	*1*
Hofstede's cultural model	*1*
Schwartz's theory of basic human values;	*1*
Social Comparison Theory	*1*
Unified theory of acceptance and use of technology	*1*

Appendix C. List of analysis carried out in the articles



Chapter II. “Who Are The People In Your Neighborhood?”: The Embeddedness of Social Links in the Era of Online Intelligent Agents

Abstract

Postmodern consumers are often described as unbounded to any form of social aggregation, such groups or communities, and the individual fragmentation appears to be fostered by the development of e-commerce platforms and new technologies. Nevertheless, the individual instances are now associated to implicit networks of influence (i.e. neighbourhoods), generated by recommendation agents, such as recommender systems, with the aim to provide a tailor-made experience and increase the predictability of future behaviours according to the preferences elicited by similar users. This research explores such implicit social influence networks investigating how they are enabled by neighbourhood-based collaborative filtering, their structure and the role of actors within them. The findings, based on a Network Analysis of 37,427 Amazon's users, 1,300 products and a correlation analysis carried out to estimate a set of centrality and community-driven measures, shed light on practically relevant implications for managers regarding the refinement of targeting activities to reach users with bridge roles within the networks and convey marketing messages to thousands of users while reducing marketing costs.

Keywords – Recommendation Agents; Implicit Network of Influence; Social Network; Weak Ties; Customization

Paper type – Research Article

Introduction

In the postmodern zeitgeist, consumers are often described as unbounded to any form of relationship, whether they be communities or modern aggregations, and freed from restricting limits of social bonds (Cova, 1997). The mobility characterizes the actions of individuals both on the spatial and social level (Bardhi and Eckhardt, 2017) and social aggregates leave room to a growing individualism (Cova, 1997). Consumers are now observed as chameleons with a low likelihood to predict their behaviour due to the free choice enabled by the postmodernism ideologies and new technologies (Cova, 1997) and, over time, the unpredictability has been also discussed as a way to represent multiple consciousnesses of individuals which alternate themselves according to the function that must be fulfilled (Cova et al, 2013; Cova, 1997; Elliott, 1993). Indeed, the postmodern condition allow for multiplicity (Cronin et al., 2014; Firat et al., 1995), and for "the experience of what is different, even paradoxically opposed" also thanks to the consumption (Firat et al., 1995, p. 43). Consumers creates self-narratives in a context of an identity mixture, along the contraposition between passive consumption versus active customization, heterogeneity versus uniformity and individualism versus tribalism (Skandalis et al. 2016; Kozinets, 2010; Cova, 1996). In this context, the experience of consumption allows for the acquisition of meanings along such contraposed existences (Skandalis et al. 2016; Cova, 1996; Firat et al., 1995).

Others have begun to rectify such view, discussing that the postmodern individualism is transitional period toward an everlasting search of new social links (Bauman, 1992; Maffesoli, 1988, 1990, 1992, 1993). In this social and individual disaggregation, people are increasingly approaching objects and services with the aim of defining their own identity (Firat et al., 1993), and veritable social hybrids, quasi-objects and quasi-subjects, reflect the system of consumption and are progressively replacing the others in the process of the identity creation (Latour, 2005). The phenomenon is wide spreading through the development of the virtual sphere and new digital technologies which favour communication and consumption while paradoxically imposing themselves as "anti-link" instruments able to increase the isolation (Escobar, 1994).

Such object-enabled solipsistic view is confirmed also by the advent of recommendation agents, as recommender systems, which by enhancing the dimension of the individual choice, based on the recommendation of items of interest, need to derive implicit social links that are created among individuals with similar preferences, regardless of their mutual awareness in the physical world (Gai et al., 2019; Ansari et al., 2000). Recommendation agents collect individuals instances, provide customized suggestions based on users' interests while implicitly associate them to neighbourhoods of consumers with similar preferences who trigger the recommendation process conveying marketing messages to other like-minded users (Gai et al., 2019; Aggarwal 2016; Ricci 2015; Ansari et al., 2000). When an unknown users, similar to others in terms of bought products, clickstream and page views demonstrates a new behaviour in the virtual sphere, he/she is automatically suggesting a new item to buy, a "frequently bought together" combination of items or a "may also like" product to other similar users (Gai et al., 2019; Aggarwal 2016; Ricci 2015). A process that enhance the individualism with its customization instances, while generating new implicit social influence networks with the aim to increase the predictability of future behaviours of the users (Ansari, 2000). Consequently, recommendation agents (RAs) function as explicit anti-link instruments able to enhance the individualism, according to the definition of Escobar (1994), while implicitly reproducing the transition to new social links (Bauman, 1992; Maffesoli, 1988, 1990, 1992, 1993).

Many companies, such as Spotify, Netflix, Amazon, TripAdvisor and Ebay, are now providing consumers with recommendations generated by RAs and heavily invest in such systems for an estimated global spending of $5.9 billion in 2019 (International Data Corporation, 2019). However, over time, marketing scholars have mainly focused on RAs discussing the effects on consumer-decision making process (Wang et al., 2007; Xiao et al., 2007) and the implied computational methods (Gai et al., 2019;Xiao et al., 2007) whereas, to the extent of my knowledge, the investigation of the implicit networks of influence enabled by recommendation algorithms, the connection among neighbourhoods (Aggarwal 2016; Ricci 2015; Ning et al., 2015), the users within the network and their role in wide spreading marketing messages have not been clarified and it is not obvious whether dominant users exists in these implicit structures that aim at favouring customisation processes while deriving implicit links among users with shared similarities in terms of online behaviours.

In the remainder of this article, I (1) present a discussion about recommendation agents, (2) their role in the decision journey and through (3) an analysis of a real-world RAs-enabled network of 37,427 Amazon's users and 1300 products (4) I assess how such agents enable implicit networks of influence inhabited by neighbourhoods of users and (5) the role of consumers in such networks. Therefore, the results emphasize the nature of RAs-enabled networks, identify most influential users in wide spreading recommendations, according to a set of centrality and community-driven measures, and some relevant managerial implications are highlighted.

Theoretical Background

Recommendation agents

Recommendation agents amplified the concept of Mass customization posited by Pine (1993), providing personalized product information, summarizing community opinions and critiques (Senecal, 2004 and 2005; Schafer, 2007) while changing the digital experience in a tailor-made path built on users preferences, elicited explicitly or implicitly, and generating recommendations accordingly (Ansari et al, 2000; Aggarwal, 2016; Cheney-Lippold, 2011). RAs minimize the risk of making an unsatisfying decision and are designed to reduce search costs and increase the chance to find products that match users' interests and preferences (Hofacker et al., 2016). Typical instances of how recommender agents are placed on e-commerce are represented by statement as "you may also like" or "People who bought this also bought" that online buyers typically encounter during their online purchase.

A widely accepted taxonomy divided the nature of RAs into two categories, the basic models (Ansari et al., 2000; Iacobucci et al., 2000; Senecal et al., 2002); Burke, 2002; Schafer, 2007; Montgomery, 2009; Pathak, 2010; Konstan, 2012; Bobadilla, 2013; Aggarwal, 2016) and domain-specific models (Liu et al., 2011; Adomavicius et al., 2013; Aggarwal, 2016; Zanker et al., 2019). The basic models mainly rely on (1) the user-item interactions, such as ratings or buying behaviour, and (2) the information associated to users and items such as their profiles and metadata (Aggarwal, 2016). Whereas, in domain-specific recommender, the algorithm takes into account different forms of data, such as temporal data, location-based data, and social data (Liu et al., 2011; Adomavicius et al., 2013; Aggarwal, 2016; Zanker et al., 2019).

As regards the basic models, the most researched methods, according to their effects on the consumer decision-making process and the implied computational methods, are the collaborative filtering, content-based and hybrid filtering (Wang and Benbasat, 2007; Xiao and Benbasat, 2007). Among the collaborative filtering methods (CFs), the most adopted by e-commerce sites are the neighbourhood-based collaborative filtering which are based on the assumption that similar users display similar patterns of rating behaviour and similar items receive similar ratings. The logic underlying the two types of neighborhood-based algorithms, user-based CFs and item-based CFs, (Aggarwal, 2016) allows to collect user's preferences for a set of items and then match users with similar ratings and make recommendations accordingly (i.e. Amazon)(Gai et al, 2019, Aggarwal, 2016; Ricci, 2015). Whereas, the content-based filtering methods makes recommendations based on users' preferred product features (i.e. in a RAs-mediated e-commerce, if the user bought some fiction films in the past, the algorithm will recommend a recent fiction film that he has not bought yet) (Choi et al., 2015; Arazy et al., 2010). While, hybrid methods involve the combination of collaborative and content-based methods with the purpose to overcome the limitations deriving from pure systems (Aggarwal, 2016).

The data nurturing the input process of recommendation agents derive from users' preferences through an implicit or explicit elicitation (Gai et al., 2019; Aggarwal, 2016; Ricci et al., 2015). The implicit elicitation regards the inference of users' preferences during their interactions with the e-tailer's ecosystem (i.e. page viewed, browsing history, product bought)(Oard et al., 1998). Conversely, the explicit elicitation process requires an extra-effort to the users, who are asked to provide an evaluation on the preferred features, categories and items (such as in the Netflix account set-up phase) (Aggarwal, 2016).

Hereinafter, I use the term recommendation agents (or RAs) and recommendation agents to describe the neighbourhood-based collaborative filtering as the most widely adopted methods in e-commerce platforms (such as Amazon, Netflix, Ebay, Spotify) to recommend products.

The role of implicit companions in the social costumer journey

The assumption behind RAs is that a hidden traveling companions with similar interests can permanently influence the customer's journey of his neighbours. A premise that reflects the shift in information search processes enabled by the technology and describes how many consumers are now the go-to source for product information (Hamilton et al., 2021). Indeed, recommendation agents propose a remediation (Bolter, 1996) beyond the physical presence of WOM recommendations typically encountered between consumers and mimic WOM recommendations using the opinions of like-minded people to generate suggestions about products and services (Ansari et al., 2000; Guttman et al., 1999). The similarities between traditional WOM processes and those enabled by RAs (Ansari et al, 2000), could be discussed drawing on the three-level process proposed by Kozinets (2010) who defined a sequence of models currently coexisting.

(1) In the Organic Interconsumer Influence Model the WOM is defined as organic and refers to the mere interaction between two consumers, without any action by marketers either in terms of communication activities or analytics. What drives individuals to recommend an item is the desire to help others, to alert them to bad service and/or to communicate a status (Kozinets, 2010; Arndt, 1967; Engel, Kegerreis and Blackwell, 1969; Gatignon and Robertson, 1986).

(2) In the Linear Marketer Influence Model the influence is activated by opinion leaders and on the attempts of marketers to influence and reach them. Consequently, the opinion leader would appear to be "the friend who recommends an already tested and reliable product" rather than "the seller who tries to get rid of the goods" (Kozinets, 2010; Dichter, 1966);

(3) The more recent Network Coproduction Model, coincides with the development of the Internet and focuses on the role of consumer networks, groups and communities (Kozinets, 2010; Cova and Cova, 2002; Hoffman and Novak, 1996). In this circumstances, consumers are considered active co-producers of value and shared meanings within their community.

In the newly RAs-mediated environments, the intentional influence that companies exert on consumers is conveyed also through recommendation systems (i.e., collaborative filtering) (Ansari et al., 2000). The prior assertion of coproduction, focused on the role of consumer networks, groups and communities, and on the recognition that messages and meanings are exchanged between community members, is rediscussed according to the logic underlying recommendation agents whereby individuals with similar preferences will not only compare their opinions or evaluations, as in physical circumstances, but will receive tailored recommendations according to their behaviour and the shared similarities with their neighbours (Ning et al., 2015). Also, in recommendation agents the recommendations are not activated on the basis of the messages sent by opinion leaders or peers, but on their actions, on shared purchase histories and the browsing patterns which are then transformed by the algorithm into a textual recommendation relevant for the user's interests (Aggarwal, 2016). Thus, exploiting RAs, users can be triggered by marketers to become a behavioural driver of recommendation (Ansari et al., 2000). The recommender engines analyse consumers' purchasing patterns, process them according to the similarities with other users and create a recommendation in textual form that aims to suggest to other similar consumers the products that are related to their interests (Ansari et al., 2000). In Figure 1, I synthesized how recommender engines acts as filters between the recommendation and the consumption activities of the users. Considering the role of marketing mix described by Kozinets (2010), these recommendation agents act both on consumers who trigger the process (i.e. the activators) and on those who receive recommendations (i.e. receivers). The activator, also under conditions of direct or indirect influence, provides the input feeding the recommender engine with data, the engine analyses the main patterns among the users and the receiver will get the recommendation in the form of a text message (Gai et al. 2019; Aggarwal, 2016; Xiao and Benbasat, 2007). Furthermore, when users are already combined in neighbourhoods the process remain unchanged since the process starts from the user within the community. Such participative approach based on the mutual cooperation between firms and consumers allow the creation of new meanings, knowledge and new products to recommend, redefining the standard concept of co-creation (Ramaswamy and Ozcan, 2018; Zaborek and Mazur, 2019). While classical co-creation leverages on consumer knowledge to develop new products (Bogers et al., 2010), focuses on the role of consumers as both innovators and consumers and the consequent benefit for other consumers (Cossío-Silva et al., 2016; Cova and Dalli, 2009), in RAs-enabled recommendation processes, consumers implicitly participate to the process automatically allowing the flows of messages among consumers. Technological artifacts, such RAs, provide interactive platforms that allow companies to collaborate with consumers, enhancing their interactional capacity (Claffey and Brady, 2014). According to Ranjan and Read (2016), such collaboration refers either to implicit value co-production (i.e. consumer–firm interaction based on the mutual exchange of physical and mental resources) and value in use (i.e. a post-purchase consumer evaluation of products based on aptitudes and knowledge).

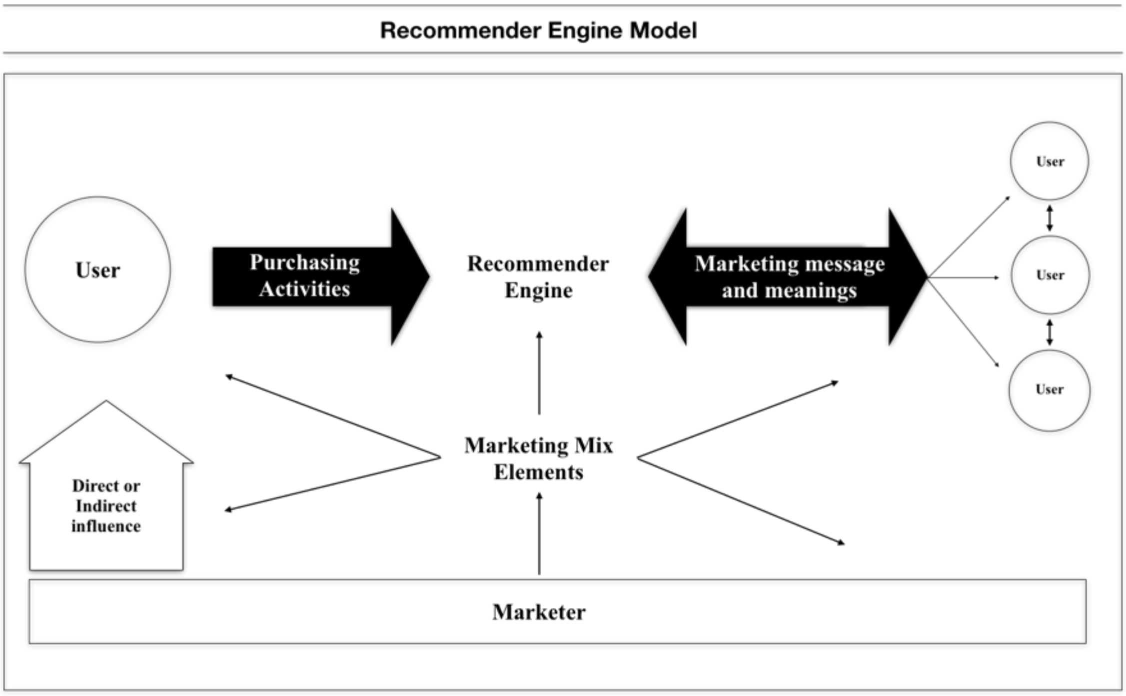


Figure 1. Recommendation process enabled by RAs

According to Senecal's (2005) assertion, a new area of research has been outlined, the one of impersonal sources that provide personalized information (Alba et al., 1997; Ansari et al., 2000; Häubl e Trifts, 2000; Guttman et al., 1999) and these agents permanently modified the recommendation process and created a new coexistent recommendation model with those already discussed by Kozinets (2010). Such technology substitutes individual's role of information gatekeepers, experts, and possibly even decision makers (a type of outsourced journey, per Lee et al. 2018) and becoming more proximal and familiar with consumers' interests, recommendation agents may be seen as more proximal social others by some consumers conveying customized marketing massages (Hamilton et al., 2021). Also, Lee (2018) posited that AI agents, are useful when individuals delegate the shopping process to someone else, such as to a product recommendation engine or to a close friend or family member, a personal shopper (Aggarwal et al., 2008). When consumers decide to consult and follow the product recommendation, they are relying on an alternative decision-making (Olshavsky, 1985; Rosen and Olshavsky, 1987) and RAs, as an external information source, increase their efficiency when consumers do not have a preferred option or are unaware of product alternatives (Senecal et al., 2005). Whereas, if consumers decide to consult product recommendations and not follow them, they are facing an owned-based decision-making (Senecal et al., 2005 ; Olshavsky, 1985; Rosen and Olshavsky, 1987). Those who adopt owned-based decision-making processes can be influenced by the recommendations but, at the same time, do not rely on them to make decisions. For example, a consumer can ask a friend about the most important attributes to consider for a given product [Price and Feick, 1984], but can also collect complementary information from other sources such as advertising, stores and sellers to determine the relevant attributes of the product to be considered.

Furthermore, a plethora of studies discussed the effects of RAs demonstrating that these agents reduce search costs supporting consumers in the identification of items with a high fit with users' interest in a vast collection of products (Resnick and Varian, 1997), influence users' consideration set (Court et al., 2009) diminishing the number of product considered (Haubl and Murray, 2006; Haubl and Trifts, 2000; Swaminathan, 2003), increase the decision quality and reduce decision efforts in large assorted platforms (Haubl and Murray, 2006; Haubl and Trifts, 2000; Pedersen, 2000), influence user's opinions and choices (Senecal, 2005; Senecal, 2004) while their impact varies according to the methods used to recommend (Diehl et al., 2003), the product categories (Senecal and Nantel, 2005) and the form of explanation involved to suggest the product (Sinha and Swearingen, 2001).

Although their effects on decisions steps are widely investigated and the effectiveness appears confirmed by the adopters (such as Amazon, Netflix or Spotify)(Gai et al., 2019), for their nature RAs affect all other steps of the decision journey. In the predecision phase (Hamilton et al. 2021) trigger consumers with new item of interest, provide them with relevant recommendations in the information search step and suggest the products that could be of interest for the user in the evaluation phase (Häubl et al, 2000). In the postdecision phase, they utilize the feedback provided by the user to give back recommendation to other like-minded individuals (Xiao and Benbasat, 2007) (see Figure 2).

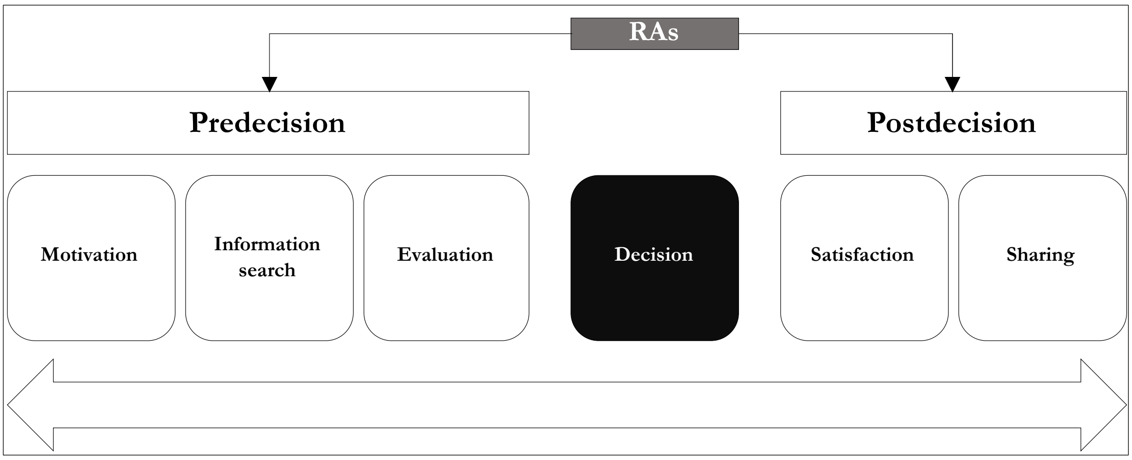


Figure 2. Effects of RAs on consumer decision journey (Adapted from Hamilton et al. 2021)

An embedded object-enabled individualism

The increasing interactions among individuals and technological objects, both at the physical and virtual level, have been also discussed in a recent stream of theories with the aim to provide a updated view of the links built between agents and consumption. Indeed, Hoffman and Novak (2018), drawing on DeLanda's assemblage theory, described the part-whole interaction between consumers and objects, whereby four types of interactions among consumers, parts and wholes exist: 1) the consumer-centric part-part interactions between consumers and objects, 2) the consumer-centric part-whole interactions between consumers and assemblages, where the consumer is one of the components of the assemblage, 3) non consumer-centric part-part interactions between objects and objects, and 4) non consumer-centric part-whole interactions between objects and assemblages, where the object is one of the components of the assemblage. Such assumption consider the relevance of the mutual effects that objects and humans exerts to each other while creating a new experience emerged from the assemblage, the interaction among heterogenous parts and neither reducible to the single components (Hoffman and Novak, 2018). According to the authors, RAs are an assemblage of components, involving objects and consumers that interact with each other through their capacities (e.g DeLanda, 2011, 2016). Also, RAs lie on an experience generated by the consumer-object interaction and convey marketing messages according to the input provided by consumers.

The preceding discussion is consistent with the Latour's Actor-Network theory (2005) that supports the part-whole interaction, while focusing on the formation of the identity of objects as a results of the relationships with humans and describing that technological artifacts, intended as social objects, exert a dual function, as intermediaries and mediators. For the intermediaries the output is predicted by the input in a causal relationship which imply a specific effect considering a predefined cause (Latour, 2005). Whereas, for the mediators, the input is never a good predictor of the output: they transform, translate, distort and even modify the meaning or the elements they are supposed to carry. A properly functioning recommender agents could be taken as a good case of a complex mediator which turn a huge quantity of data associated to users in personalized recommendation based on users' and neighbours' preferences (Ning et al, 2015). In the same vein, drawing on models of object agency including assemblage theory (DeLanda, 2016) and actor network theory (e.g., Latour 2005), the RAs exert their agency affecting, and be affected by, consumers (Franklin and Graesser 1996), are autonomous because they function independently and has the authority that allows them to control other entities and make its own decisions (Parasuraman et al. 2000). Thus, these recommendation objects affirm their social agency generating effects on the surrounding world through an intentionality inherent in the code – and aimed at recommending items of interest – while potentially prompting the individual to perform certain actions according to his preferences and those of his own neighborhood (Ning et al., 2015).

The concept of neighborhood has been widely discussed in WOM literature, and firstly introduced by Muniz and O'Guinn (2001) to classify restricted groups of individuals which are inhomogeneous with respect to other groups but similar within the cluster and with a reduced feeling of "we-ness". Neighborhood are linked by temporary interests, few ties and define themselves in contradistinction to another community (Muniz et al., 2001). Whereas, communities differ from neighbourhoods, since a consciousness of kind is shared among individuals, which describes the perceived membership of participants and intersects with the identity (Bagozzi & Dholakia, 2006a). The members of communities feel connected with other members, and separate themselves from outsiders (Bagozzi & Dholakia, 2006b), derive a feeling of belonging from their membership to the community (Algesheimer et al., 2005), also through the activation of shared ritual and traditions, and create a singular meaning of the community within and over the borders (Casaló et al., 2008).

Charactheristics	Neighborhood	Community
We-ness	Low	High
Links	Temporary	Durable
Consciousness of kind	Low	High
Perceived membership	Low	High
Feeling of connection	Low	High
Rituals	Absent	Present

Table 1. Comparison between Neighbourhoods and communities by characteristics

Also, in accordance with Arvidsson e Caliandro (2016), neighbourhoods are nowadays proliferating within the so-called "hackerdom", a context enabled by new technologies, such as open source platforms or online agents, which allow to generate implicit and explicit connections among individuals who come into contact with them (Arvidsson et al., 2016). Similarly, neighbourhoods enabled by RAs do not rely on a feeling of we-ness since are implicit, change over time because their membership is a function of purchases (Ning et al., 2015) and are connected with other neighbourhoods through the links that few users share. Recommendation algorithms work as automated processors which links users, unbeknownst to them, according to their demonstrated preferences. An intriguing functioning that allow to reside in an implicit neighborhood which, in turn, is often unaware that is conveying marketing messages every time a neighbor make an action (Dellarocas, 2003).

The embeddedness of social links in the new social costumer journey

The role of new implicit network of influence has been discussed by Hamilton et al.(2021) describing a new social costumer journey which recognize the role of the others and of new technologies, such as intelligent agents, in redefining the concept of social closeness. However, authors posited that social others (i.e., traveling companions) can influence individual costumer's journey at various stages, while also themselves being influenced by that costumers. The type of influence could be both implicit and explicit: the influence may even be implicit, when is perceived by the focal costumer without any intention to influence on the part of the social other while the explicit influence is based on the intentionality of the sender to push the receiver toward the action (Hamilton et al., 2021; Argo and Dhal, 2020). Recognizing the role of "peer-to-peer/social" influences, the model also discusses the relevance of direct and indirect "traveling companions" in affecting shopping processes and other consumers along the social distance continuum, which goes from proximal others to distal others (Hamilton et al., 2021). Proximal others are well-known and individuated others that provide specific suggestion according to the user and the costumer's journey step, whereas "distal social others can be larger groups or the whole of society, whose members may not be individuated, present, temporally proximal, or even known to the consumer" (Hamilton et al, 2021;pp.72). Such distal others could be single individuals, such as Influencer, tutorialist, reviewers writer or algorithmic recommendation generated by recommendation agents (Hamilton et al, 2021). Although, higher proximity with social others is associated to a stronger influence than distal others, authors posited that the influence vary according to (1) the importance of more distal social influences in certain contexts; (2) changes in perceived social distance, along one or more of the dimensions, often brought about by technological changes; and (3) the nature of, rather than simply the magnitude of, the roles that proximal and distal social others may play (Hamilton et al, 2021).

These dimensions converge to form a global sense of social distance, but not all dimensions need to be on the extreme ends of the continuum for the social other to be interpreted as overall more proximal or distal. In a RAs perspective, I discuss a new form of implicit networks of influence as composed by (1) unknown individuals, in terms of awareness, but similar in terms of demonstrated behaviors, (2) a virtual and time-related presence, (3) jointed in a neighborhood and (4) in computed strength of ties according to the demonstrated differences with others users. The social distance continuum (Hamilton et al., 2021), could also be considered under the lenses of the theory of structuration in which Giddens (1984) refused the stratification of social levels while introducing a *feedback-feedforward* process through which social relationships are defined. In this model, the agency of individuals exerts a constant influence on the surrounding environment which, in turn, become the output of such interactions (Giddens, 1984). However, in a feedback-feedforward process, the individual create links with others and forms social bonds, group memberships and then, the entirety of aggregations, form the social representations and the societal structure. An approach based on three different level of analysis, micro (i.e., the individuals), meso (i.e., social groups) and macro (i.e., society at large) which influence each other in a recursive process (Giddens, 1994).

When applied to the algorithmic logic, how is the continuum of social distance formed? What are the connections that tie individuals, groups, and the whole structure?

According to the functioning of RAs, the individual act in a context that aims to understand his actions and is implicitly associated to a sequence of social links according to the shared similarities (Ning et al, 2015). At the micro-level of analysis there is the user that demonstrates a specific online behaviour which lead to the aggregation with other individuals with similar preferences, shifting the analysis on the meso-level. The entirety of groups and aggregations define the structure (i.e., macro-level) intended as the reciprocity between actors and collectivities across extended time-space. Furthermore, the algorithmic-based structure is constantly informed by individuals actions and, in line with the feedback-feedforward process, constantly refines the boundaries of social aggregations in order to create neighbourhoods with an high likelihood to find similar individuals, in terms of preferences, within them. The higher the number of feedbacks from individuals, the greater the discrimination the system creates among the neighbourhoods. The algorithmic-based social structure is also dynamic and changes according to the individuals who compose it. It means that if the human agent changes his behaviour the structure tends to associate him to new neighbourhoods whether the one in which he resides has not demonstrated the same behaviours in the past. A continuous movement leading to (1) a constant research of the homeostasis within the system and (2) to an evolution of implicit social bonds according to the demonstrated behaviours of the individual.

In this everlasting change, how can I target marketing efforts accurately? Which are the most influential individuals within the implicit network of influence?

According to extant WOM literature, the ability of an information to flow within a network has been often discussed as strictly dependent by the tie strength among individuals (Granovetter, 1973) the intensity of the relationship between consumers (Bansal and Voyer, 2000; Granovetter, 1973; Iacobucci and Hopkins, 1992) and how homophiles or heterophilies are individuals in terms of attributes, opinions and preferences (Steward and Conway, 1996; Gilly et al., 1998). Granovetter's (1973) theory of the strength of weak ties posited that under the circumstances of bounded rationality (Simon, 1957) social relationships must be taken into account in order to consider the economic agent in its entirety (Granovetter, 1973) and consumer's social relations are mainly embedded in three forms of social links with a different degree of strength: strong, weak and dormant. The strong ties are those where individuals rely on high level of trustworthiness, sense of collaboration and respect for partners while the weak ties do not account for strong links but are nonetheless productive in order to establish collaborative relationships (Granovetter, 1973). While in strong ties, information is "redundant", i.e., there is a tendency for the information circulating to be always the same (and therefore at risk of stagnation), in weak ties, information changes, is always new and allows the company or individual to take advantages such as greater information retrieval on changes, ties and the possibility of establishing ties with new partners. Although weak ties have less impact on the individual level, they lies on a greater potential to favor the flow of new external influences toward a network, wide spreading the information (Goldenberg, 2000).

As argued by Ryu et al. (2007), with weak ties, people establish fleeting relationships, driven primarily by self-interest and do not feel any special responsibility for the other person. They prefer balanced relationships based on the mutual exchange. If not, they try to reduce what they give or increase what they receive to achieve homeostasis (Walster et al., 1973). Brown and Reingen (1987) demonstrated that the weak ties are relevant for their bridging function which allow information to travel toward dense social structure which are composed by several components. Without the existence of weak ties, a system is conceived as a sum of disjointed groups, inhibiting the widespread of information. Indeed, weak ties are more likely to spread information rather than influence consumers' decisions as strong ties do (Ellison and Fudenberg, 1995; Brown and Reingen, 1987). The effects of the ties vary according to the consumer's previous knowledge and perceived task difficulty (Duhan et al., 1997) and strong ties are more likely to be required for retrieving information about an object and has more influence on receiver's decisions (Bansal and Voyer, 2000). Also, weak ties are more relevant in wide spreading information through word-of-mouth about innovations (Rogers, 1995). Moreover, has been discussed that weak ties in online contexts are more likely to introduce newcomers in a network (Fieldman, 1993) and online social networking increase the number of weak ties which was previously dormant, lowering the barriers to participation, and maintain weak ties more easily and with less effort, (Obal 2011, Ellison et al. 2007).

Similarly, RAs creates a network structure where consumers are grouped according to the degree of their similarities in subnetworks linked within them by strong edges derived from repeated similar behaviours while between them according to the differences among neighbours (Aggarwal, 2016). Unlike other real-word networks, the ties created by RAs are irrespective to the social characteristics of an individual (i.e., gender, age, popularity) and are mainly based on the interests elicited by the user.

In my idea, as many social structures, strength and weak links be assessed also in the implicit structures enabled by RAs. Whereas, other authors (Granovetter, 1982, Friedkin,1980; Weimann, 1983) explained the role of weak ties in other consumption contexts and with limited availability of data, to the extent of my knowledge, this the first study aimed at describing RAs-enabled network and the role its users in a real-word network enabled by recommendation agents.

Conversely, strong ties has a crucial role in micro-level referral behaviour, including tie activation, information seeking and emergence of subgroups (Brown et al.,1987). Densely connected communities present repeated interactions, homogenous preferences for several goods than those who belong to other communities (Brown et al.,1987). The redundancy of communication flow in a group allow for a greater availability of others as sources information and influence (Granovetter,1983, Brown et al., 1987). Also, strong-tie consumers tend to know much more about each other than weak ties do (Belk, 1971) and present a high homophily with the others (Ryu, 2007, Brown et al.,1987; Gatignon et al., 1985; Rogers, 1983), intended as the similarity in terms of certain attributes. Moreover, strong ties are more aware of others' needs and preference since they are frequently in contact (Ryu, 2007; Granovetter, 1973) and track the evolution of their needs (Clark et al.,1986) whereas, in presence of weak ties, individuals are interested in the others' status and build communal relationships without expecting anything in return (Ryu 2007: Clark 1984; Clark et al. 1986; Frenzen et al., 1993). This lead people to be more incline to make a recommendation to strong ties than weak ties (Riu 2007, Brown et al., 1987; Frenzen et al., 1993).

Drawing on these premises, RAs-enabled implicit networks are formed by neighborhood composed by users who behaved similarly in the past and receive recommendations accordingly. In these circumstances, when a strong tie of a user (i.e. a neighbour) activate a new behaviour, it is automatically recommending a product to a similar user (Aggarwal, 2016; Ricci, 2015), while weak ties should have a peripheral role in the community functioning as a bridge from the external environment.

Considering prior evidences on the ability of weak ties to widespread information and recommendation across a larger number of groups and that strong ties are more likely to widespread redundant information and recommendation within the group they are belonging to, I therefore assume that, in RA-enabled networks:

H1: Weak ties activated for a recommendation are more likely to wide spread recommendation across a greater number of neighborhood than strong ties

H2: Strong ties activated for a recommendation are more likely than weak ties to widespread redundant information within the neighborhood

Research

Data collection

To describe the structure of implicit networks of influence enabled by Recommendation Agents I used an Amazon's public dataset of 2018 with 233.1 millions of transactions. Then, a convenience subset of gift cards items has been extracted for a total of 147,194 users and those users who were not associated to any recommendation were removed from the study resulting in a matrix of 37,427 individuals * 1,300 products. The gift card's dataset allowed to quantify the network measures since the overall size was suitable for the analysis carried out and the product involved is among the most purchased items on the platform.

The Amazon's dataset has been chosen for the wide adoption of collaborative filtering within the platform. Irrespective to other e-tailers, Amazon.com embedded its own proprietary neighborhood-based item-to-item collaborative filtering which take into account item's purchase history and users' similarities within the "Customers who bought this item also bought" section (Amazon, 2003). Furthermore, in the section "Consumers who bought this item, also bought" the platform exposes consumers to a set of recommendations defined according to how other consumers behaved in the past. A consumer who receive a recommendation about a specific PC-Cover while buying a PC, it is because previous consumers who bought a PC also bought a PC Cover. It indicates that a user who is buying a product X, would also buy a product Y because other users in the past behaved in that way.

In my study, I matched the recommendation proposed in the "Consumers who bought this item, also bought" section with each User IDs to discover the recommendations received by users and the similarities with the recommendations conveyed to other users.

Methods

To analyze the large dataset I conducted a Social Network Analysis (SNA)(Burt 1980; Emirbayer and Goodwin 1994; Granovetter 1979; Mitchell 1979; Rogers 1987; Durkheim

1960; Simmel, 1950; Moreno, 1934). The data preparation has been carried out in Python, while the processing and analysis have been conducted using "igraph" (Csardi G et al. 2006), "sna" (Butts, 2008), "ape" (Paradis, 2019), "dnet"(Fang and Gough, 2014), "Network Toolbox" (Butts,2015) and "bipartite" (Dormann et al, 2008) packages in R (R Core Team, 2017) (see Appendix 1). To deal with the large size of the network and matrices, a virtual machine with R installed has been created through AI Platform provided by Google Cloud Platform.

Since all users have been exposed to a set of recommendations, I computed a two-mode matrix adding to the columns the total number of gift cards recommended by Amazon while in the rows the users and within the corresponding cells the number of times the product has been recommended to a user (see Figure 3).

	B00BXLVZZE	B00IGYPALG	B00FTGTM5E	B075SHPN2P	B00FTJI60I	B079GCLTZM	B00FTGEXZI	B071DTXNHG
A3F44KCZ816GN2	1	1	1	1	1	1	1	1
A3M31G4GJ9066T	0	0	0	0	0	0	0	0
A35DVVHF5D00MP	0	1	1	0	1	0	0	0
A2P7PQ3G6TE8GT	0	1	1	0	0	0	0	1
A3L7FALBSLA3S	0	1	1	0	0	0	1	0
A21FCCP98J6YDU	0	1	1	0	1	0	0	1
A2I3RXUUF0J33N	0	1	1	0	0	0	0	1
A3VV44Y6WL297Q	0	1	1	0	1	0	0	0
A3O6MA878FRRRW	0	0	0	0	0	0	0	0
A2WRWI1U801TVQ	0	0	0	0	0	0	0	0

Figure 3. Matrix with UserIDs * recommended Product ASINs

The subsequent transposition of the matrix, allowed me to derive a 37,427*37,427 one-mode user-user matrix where, within the cells, the number of times two users have been exposed to the same recommendations has been computed. The diagonal of the adjacency matrix has been imposed to be equal to 0 to avoid self-loops (see Figure 4).

	A2HSD47KF0HII	AK7JS2ASR7LFF	ABGVLESCLQX85	ABQFTT7Z5OXQH	A2LL58UGFLH3PB	A32OUYZCN0QWTP
A2HSD47KF0HII	0	9	7	11	61	10
AK7JS2ASR7LFF	9	0	43	54	9	53
ABGVLESCLQX85	7	43	0	47	7	38
ABQFTT7Z5OXQH	11	54	47	0	11	54
A2LL58UGFLH3PB	61	9	7	11	0	10
A32OUYZCN0QWTP	10	53	38	54	10	0

Figure 4. Matrix with User * User and corresponding times they were exposed to the same recommendation

Subsequently, to discover whether neighbourhoods exist around the recommended products, the Multilevel community detection algorithm (Blondel et al., 2008) has been employed. The algorithm compute the communities according to the modularity. It starts attributing a different community to each node and then the node is moved to the community where achieves the highest positive contribution to modularity. This process is reiterated for all nodes until the highest modularity for the community is achieved (Yang et al., 2016). The resulting division relies on many edges within communities and only a few between them. However, the higher is the number of links between two individuals, the higher would be the likelihood to reside in the same community. According to this algorithm, when to consumers are frequently exposed to the same recommendations they will be joined into a community. Also the method is suitable for large networks since the computational complexity (O(N log N) is not quadratic (Xie et al. 2013). To assess the significance of each neighborhood, two types of degrees for each node have been computed: the degrees based on neighbours within the community itself, and the degrees based on the neighbours outside the community. Then, a two-sample Wilcoxon tests has been performed on these two types of degrees to produce the significance level.

Next, to test all of my hypothesis and to assess the role of individuals within the network, a set of centrality and community-driven measures have been involved. Whereas, to understand the role and charactheristics of individuals and the ability to wide spread marketing messages a dissemination efficacy matrix has been created taking into account the amount of times a product bought by a specific user has been recommended to the neighbourhoods. It resulted in a $N_{users}*N_{cluster}$ matrix, containing in each cell the times each product the users bought has been retrieved in the neighbourhoods.

At the end, a matrix containing a set of centrality and community-driven measures for each user has been computed. The columns of the matrix contains the measures of the position of the user within the network and its ability to spread recommendation across existing neighbourhoods. The results of the $32{,}427_{users}*7_{measures}$ matrix have been tested through the Pearson's correlation to discover whether exist significant associations among the measures.

To deal with the large dataset I drawn on Efron's (1979a,1979b,1982,1988) bootstrap method as a resampling technique. The bootstrap is suitable for quantify the uncertainty associated to an estimator allowing for the computing of confidence intervals based on multiple samples (James et al., 2014). After generating 100 random bootstrap sample with replacement $X^*_1, X^*_2, \dots X^*_{100}$ of n=1000 observations each I replicated the Pearson's correlation coefficient statistics for each bootstrap sample.

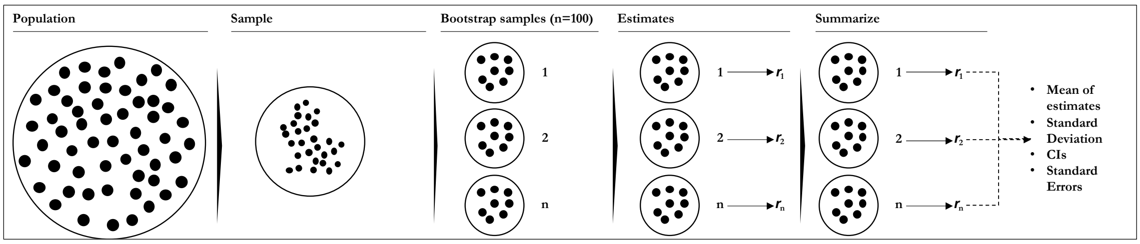


Figure 5, Bootstrap method (Efron, 1979a,1979b,1981, 1982,1988)

As a result, I obtained thousands of estimates of the Pearson's correlation coefficient which formed my bootstrap distribution. A few of the 100 bootstrap replications are shown in Table 4 and the distribution are graphed in Figure7. Then, the bootstrap distribution has been used to define the empirical estimate, the standard deviation, the confidence interval and the standard error (Efron, 1979a,1979b,1982,1988). To overcome the skeweness reported in some boostrap distribution the bias-corrected and accelerated (BCa) bootstrap interval method has been involved (Figure 3)(Efron et al., 1993).

At the end, to deal with the normality assumption I applied the Fisher's z-transformation (Silver et al., 1987) to all the bootstrap distributions to further assess through a One-way ANOVA whether relevant differences among the subsamples exist. The number of samples have been used as a categorical variables to discover how the assumed DVs vary according each level of the factor.

Network Measures

Centrality Measures

The set of centrality measures has been employed to discover the role of individuals within the network, the neighbourhoods and their relative importance. The simplest *degree centrality* have been assessed to count the connections of the individuals (i.e., edges) (Bolland et al, 1988; Marvin, 1954).

Also, the *eigenvector centrality* has been measured to assess the quality of the connections of the actor (Freeman, 1978). A higher eigenvector centrality define those nodes who are connected to most popular nodes in a network (Bonacich, 2020).

Furthermore, the *betweenness centrality* has been computed to discover the times a node is connected to the shortest path between two vertices. The higher the presence of an actor in these paths, the higher the power to control communication since several links are passing through those paths. Nodes that are present on many paths are more relevant in the communication process (Freeman, 1977, 1979, 1980).

Similarly, the *closeness centrality* has been outlined to represent the average distance, or average shortest path, to all other vertices in the network (Bavelas, 1950; Beauchamp, 1965, Sabidussi, 1966). A central actor would be close, on average, to other vertices in the network. The measure allows to evaluate if a central vertex is 'close' to other nodes. At the end, the PageRank (Brin and Page, 1998, Page, 1999) index has been involved to assesses the relevance of nodes in the network modelling the probability that a "random" node who starts at a random position in the network and continues following links, will connect to a vertex in the network.

Community-driven measures

While the prior measures are nodes-specific, a set of community-driven indicators have been adopted to discover the structure of communities and the role of individuals within them. In network analysis, a community relies on densely connected nodes and shared properties, such as friendship, like-minded individuals ore a frequent exchange of communication (Palla et al., 2007). A relevant measure that can be used to highlight relevant nodes in the community is the embeddedness (Palla et al., 2007), defined as the ratio between the internal degree (the number of connections to other vertices within the community) and the total degree (all connections, including ones with vertices outside the community).

Similarly, the participation coefficient has been computed. A vertex with edges exclusively in its own community has a participation coefficient of 0. To compute the participation coefficient the WalkTrap algorithm has been used (Pons and Latapy, 2005) and if two nodes *i* and *j* are in the same community, the probability to get to a third node *k* located in the same community through a random walk should not be very different for *i* and *j*. Values closer to 1 suggest greater within-community connectivity and values closer to 0 suggest greater between-community connectivity.

Results

Network properties and neighborhood detection

The overall diameter of the graph, which is the length of the longest path between a pair of nodes (Wasserman and Faust., 1994), is equal to 2, with an average number of steps between two nodes, equal to 1,0082 (i.e. mean distance). Such results demonstrate a high-densely connected network of users linked by each other through the recommendation they have been exposed during their shopping activities. Indeed, 694,560,660 edges have been retrieved among 37,427 users and 1300 products leading to an overall density of 0.9917. The graph density is measured in a range that goes from 0 to 1 and represents a continuum that goes from the absence of connections to all actors connected. In such case, the majority of users are connected among them but with different weights, suggesting that according to the logic underlying the RAs, different relationships among users due to the degree they were exposed together to some recommendations exist. Indeed, subsequent graph measures describe such evidence.

The average degree of each node is 37,118 indicating the unique number of nodes that each user is interacting with. It suggests that each users has the 99% (i.e. 37,118/37,427) of probability to be found connected to another user thanks to the messages conveyed by RAs, indicating that the majority of users have been connected to all other nodes because of the same exposure to at least one recommendation. Also, this measure could describe the (1) novelty characteristics (Aggarwal, 2016) of an RAs which prompt the algorithm to recommend products never viewed before regardless the elicited interests of the user and (2) the limited assortment which lead the algorithm to recommend the available products.

	Nodes	Weighted Edges	Diameter	Mean Distance	Density	Avg. Degree	Avg. Strenght	Avg. Participation Coefficient	Avg. Betweenness Centrality
Network Graph	37,427	694,560,660	2	10.082	0.9917	37,118	1,018,888	0.5003	17,774.08

Table 2. Network measures

Although, the Amazon's network is highly connected and all users have the 99% of probability to be connected with another, the strength of relationships measure has been involved to define the degree through which two or more users are exposed to the same implicit network of influence enabled by the RA. In fact, the average strength of each node, also indicated as the number of edges going from one node to another, is equal to 1,018,888 divided across the previous 37,118 average links in a different degree. It indicates that $User_1$

and $User_2$ could have been connected 100 times while $User_1$ and $User_3$ only 2 times. The higher is the weight of the connection between two users, the higher will be the number of times they have been exposed to the same message.

Indeed, the average participation coefficient, intended as the strength of a node's connections within its community, is equal to 0.5003, with a minimum of 0.5 and a maximum of 0.501. It indicates there is a part of users which are frequently exposed to the same messages and are highly embedded within the communities, while another part of them tend to be connected with other neighbourhoods reporting a low within-community connectivity. However, considering 1 as an indicator of greater within-community connectivity and values closer to 0 as a measure of greater between-community connectivity, RAs enabled community slightly tend to 1. Such result, also explain the structure of RAs-enabled implicit network which mainly tend to combine users in neighborhood.

Furthermore, the average shortest paths between two nodes that pass through a particular node (i.e. betweenness centrality) is equal to 17,774 indicating that a node is, on average, 17,774 times in the middle of the path between two nodes.

At the end, users within the network are densely connected among them and this could be due to the assortment of products in absolute terms or the ability for users to drive messages at the same manner. However, potential differences in terms of strength of ties are highlighted according to the participation coefficient and the average strength indicators, suggesting that further substructures within the network and different roles within them could be discovered.

In this vein, to further discover the structure of the network and the links which tie individuals, I ran the Multilevel community-detection algorithm to assess the existence of communities according to their modularity (Blondel et al., 2008). The resulting communities are composed by those individuals that are more connected among them and disconnected with regards to other communities. Furthermore, the density within a community, due to the average strength of links among individuals, should be higher than the total density of the network.

As shown in Figure 6, 14 densely connected neighborhood have been found with an overall density higher than the density of the entire graph. For each community of the graph, two types of degrees for each node have been calculated: the degrees based on links within the community itself, and the degrees based on the members available in the graph. Then, a two-sample Wilcoxon tests has been performed on these two types of degrees to produce the significance level. As a result, all neighbourhoods are significant at $p<0.001$(***) level.

#Neighborhood	Size	Density	Significance	Modularity
1	980	0.990	***	0.048
2	4983	1.000	***	0.048
3	579	1.000	***	0.048
4	2083	1.000	***	0.036
5	5933	1.000	***	0.036
6	5005	0.999	***	0.036
7	1148	1.000	***	0.036
8	6847	0.999	***	0.046
9	116	1.000	***	0.046
10	2160	1.000	***	0.046
11	1365	1.000	***	0.046
12	234	1.000	***	0.046
13	5917	1.000	***	0.046
14	77	1.000	***	0.000

Table 3. Number of significant neighbourhoods available in the network and related measures

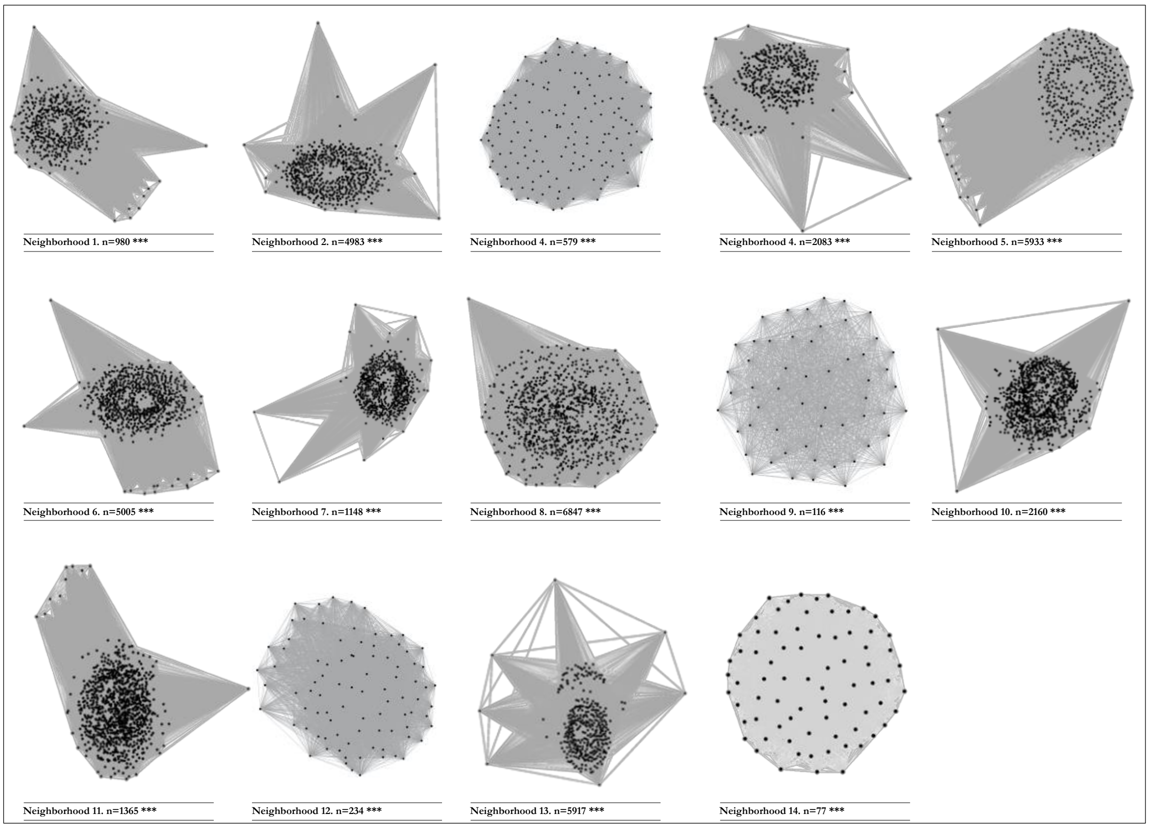


Figure 6. Number of significant neighbourhoods available in the network

Observing the 14 neighbourhoods a high connections among actors in the majority of neighborhood is highlighted and a recursive appearance of peripheral users within each subgraph is reported. Such nodes are potentially less linked to the members of the community due to their peripheral role and they could be probably exposed to link with external users of other communities. Such individuals could interact with nodes in other networks and brings the information from the external context to the internal environment (Vikatos et al. 2020, Corradini et al. 2020, Granovetter, 1973; Burt, 1992; White, 1970) and could function as a bridge to spread the marketing message among a higher number of communities while the users embedded in their communities are more likely to generate a redundancy in the message receiving and delivering same messages within the community (Granovetter, 1973).

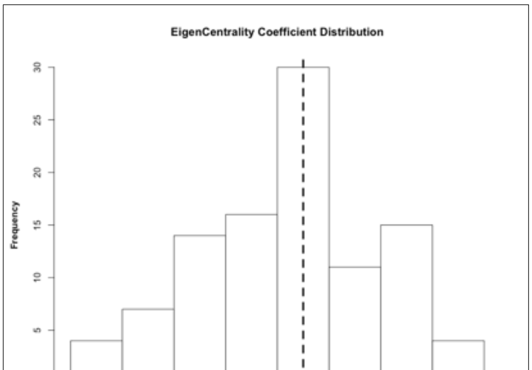
Nodes' measures and dissemination efficacy

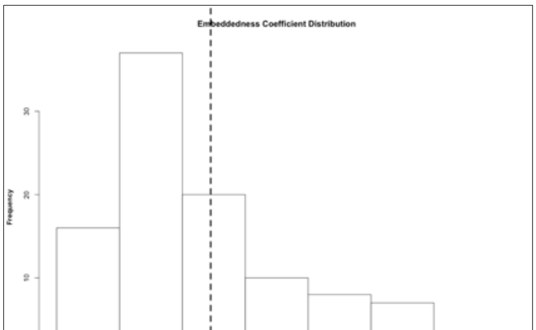
To test whether peripheral positions could be associated to higher degrees of message dissemination and my hypothesis, I proceeded collecting the centrality and community-driven measures for each single user. Such metrics allowed me to (1) test my hypothesis, (2) describe the status of each user within the network and (3) define their role in spreading recommendations among other users and neighbourhoods.

As discussed in the Methods section, I ran a bootstrap-based resampling techniques (Efron, 1979a,1979b,1982,1988) to assess the Pearson's correlation coefficient estimate between dissemination efficacy and the other measures along the 100 sample of n=1000 observation each. As shown in Table 4 the bootstrap distribution for coefficients for each subsample and the relative CIs have been reported.

Bootstrap Sample b	$r_{EigenCentrality}$	$r_{Embeddedness}$	$r_{ParticipationCoefficient}$	$r_{DegreeCentrality}$	$r_{ClosenessCentrality}$	$r_{BetweennessCentrality}$	$r_{PageRank}$
1	0.44 [0.39;0.50]	-0.61 [-0.66;-0.55]	-0.39 [-0.45;-0.33]	0.40 [0.34;0.47]	0.55 [0.49;0.62]	0.47 [0.41;0.54]	0.54 [0.48;0.60]
2	0.40 [0.34;0.46]	-0.56 [-0.62;-0.5]	-0.23 [-0.29;-0.17]	0.38 [0.32;0.44]	0.56 [0.50;0.62]	0.47 [0.41;0.53]	0.50 [0.44;0.56]
3	0.48 [0.34;0.46]	-0.37 [-0.62;-0.5]	-0.34 [-0.43;-0.28]	0.41 [0.37;0.47]	0.57 [0.50;0.62]	0.47 [0.41;0.53]	0.58 [0.52;0.63]
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
50	0.42 [0.36-0.48]	-0.57 [-0.63;-0.51]	-0.37 [-0.44;-0.31]	0.40 [0.33;0.46]	0.45 [0.39;0.52]	0.48 [0.41;0.54]	0.53 [0.47;0.59]
51	0.36 [0.30-0.42]	-0.39 [-0.46;-0.33]	-0.46 [-0.52;-0.31]	0.40 [0.33;0.46]	0.36 [0.30;0.52]	0.47 [0.40;0.53]	0.46 [0.40;0.52]
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
99	0.42 [0.38-0.5]	-0.11 [-0.17;-0.05]	-0.41 [-0.47;-0.35]	0.38 [0.34;0.46]	0.34 [0.28;0.40]	0.47 [0.40;0.52]	0.50 [0.48;0.60]
100	0.42 [0.36-0.48]	-0.44 [-0.50;-0.38]	-0.42 [-0.48;-0.36]	0.39 [0.32;0.45]	0.39 [0.33;0.45]	0.48 [0.41;0.54]	0.51 [0.44;0.56]

Table 4. Bootstrap distribution of each network measure and the corresponding mean of Correlation Coefficients





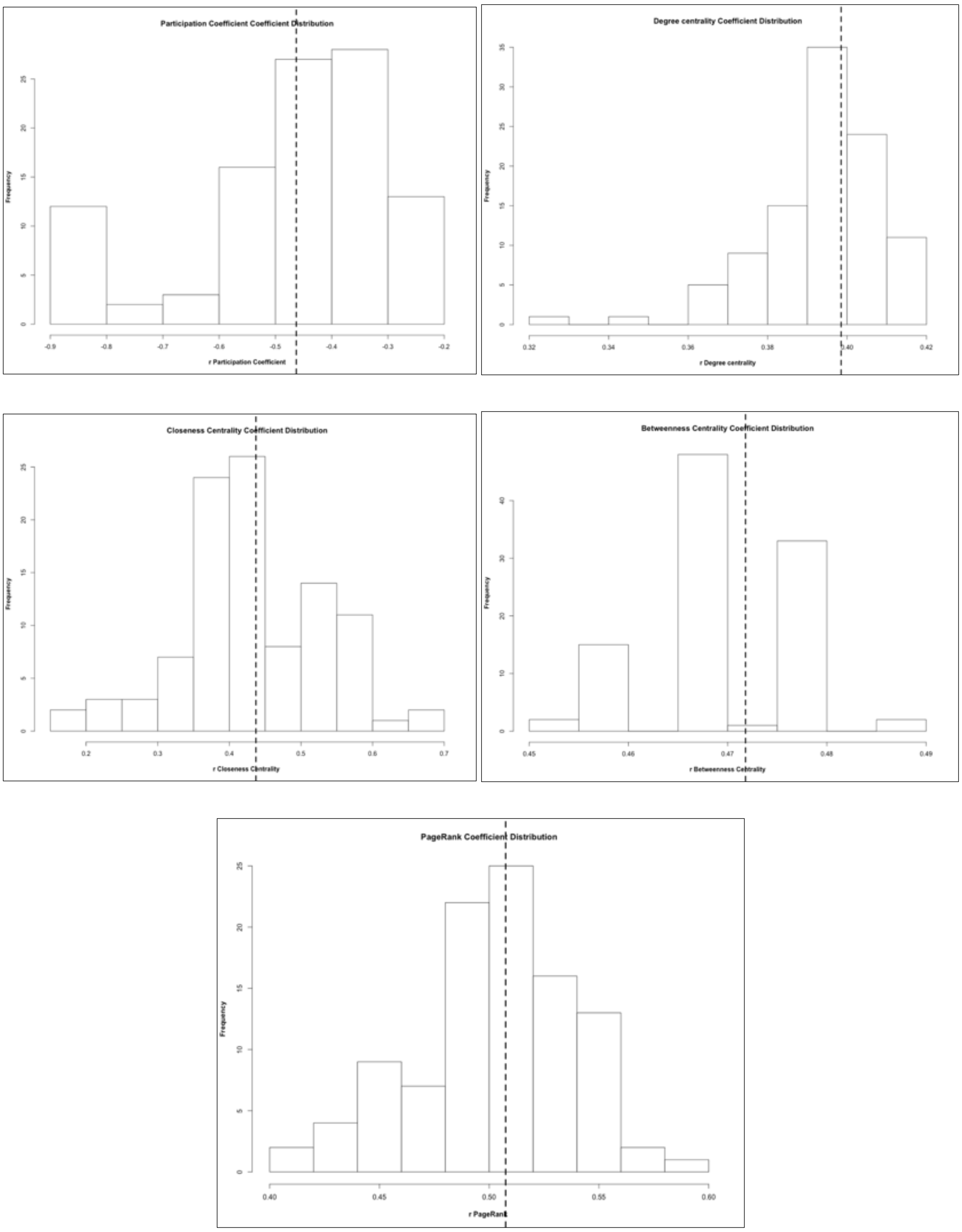


Figure 7. Bootstrap distribution of each network measure and the corresponding mean of Correlation Coefficients

Subsequently, I proceeded computing the 95% CIs and the standard errors of all bootstrap distributions using the bias-corrected and accelerated (BCa) bootstrap interval (Efron and Tibshirani, 1993). Hence, through the procedure I obtained the 95% CIs for each measure, associated standard errors and the average estimate.

	$r_{EigenCentrality}$	$r_{Embeddedness}$	$r_{ParticipationCoefficient}$	$r_{DegreeCentrality}$	$r_{ClosenessCentrality}$	$r_{BetweennessCentrality}$	$r_{PageRank}$
Estimate (SE)	0.41 (0.003)	-0.45 (0.015)	-0.46 (0.018)	0.39 (0.002)	0.43 (0.010)	0.472 (0.001)	0.508 (0.004)
CI s	[0.391;0.414]	[-0.482;-0.423]	[-0.500;-0.430]	[0.395-0.401]	[0.418;0.456]	[0.470;0.473]	[0.500;0.515]

Table 5. Mean of estimates and CIs

In a further test, I analyzed the mean differences of the estimates among the 100 subsamples through a One-way ANOVA after adopting the Fisher's Z-transformation for each distribution to respond to the normality assumption. As shown in Table 6, all *p-value* are not statistically significant, indicating that coefficients do not vary significantly across the level of the categorical variable.

	$r_{EigenCentrality}$	$r_{Embeddedness}$	$r_{ParticipationCoefficient}$	$r_{DegreeCentrality}$	$r_{ClosenessCentrality}$	$r_{BetweennessCentrality}$	$r_{PageRank}$
SS	0.005	0.0004	0.028	0.0002	0.0017	0.0001	0.0029
MS	0.005	0.0004	0.027	0.0002	0.0017	0.0001	0.0029
F	2.946	0.014	0.508	0.849	0.143	1.704	1.817
p	0.08	0.90	0.47	0.359	0.70	0.19	0.18
Df	(1;99)	(1;99)	(1;99)	(1;99)	(1;99)	(1;99)	(1;99)

Table 6. Results of One-way ANOVA

As a result, the *r* Eigen Centrality estimate reported a mean of 0.41, a value that is included in the 95% of the samples since the CI's lower level is equal to 0.403 and the upper level is equal to 0.417. Similarly the embeddedness (M$r_{embeddedness}$= -0.45; [LL:-0,482;UL:-0.423]), participation coefficient (M$r_{\text{participationcoefficient}}$ = -0.46; [LL:-0,500;UL:-0.430]), degree centrality (M$r_{\text{degreecentrality}}$ = 0.39; [LL:0,395;UL:-0.401]), closeness centrality (M$r_{\text{closeness centrality}}$ = 0.43; [LL:0,418;UL:0.456]), betweenness centrality (M$r_{\text{betweenness centrality}}$ = 0.472; [LL: 0,470;UL:0.473]) and PageRank (Mr_{PageRank} = 0.508; [LL:0,500;UL:0.515]) do not vary significantly across the bootstrapped samples and all the reported means are contained in the 95% of them.

Drawing on these results, a positive significant association between dissemination efficacy and Eigen Centrality has been assessed (*r* =.41, CI[0,403;0,417]. It indicates that the higher is the connection of a vertex with most influential nodes, the higher is the ability to spread a recommendation in more neighborhood after the purchase. Conversely, there is a negative correlation between the dissemination efficacy of a user and the embeddedness in a neighbourhood ($r_{embeddedness}$= -0.45; [LL:-0,482;UL:-0.423]). These results suggests that a user with several ties in a community tend to spread less messages than users with a low level of embeddedness, indicating that a more peripheral position in the neighborhood enhance the ability to spread the recommendation to a greater number of communities. Similarly, the participation coefficient, which measure the strength of a node's connection within its community, is negatively correlated to the dissemination efficacy ($r_{participationcoefficient}$ = -0.46; [LL:-0,500;UL:-0.430]). The higher is the within-community connectivity, the lower is the ability of a user to spread the message across different neighbourhoods. On the other hand, users with an high degree centrality in the network are more likely to spread recommendations more than users with a low degree ($r_{degreecentrality}$ = 0.39; [LL:0,395;UL:-0.401]). It indicates that the ability to spread a message across different communities increase with the level of popularity (i.e. the number of edges) of a node. Moreover, a positive correlation coefficient has been found between dissemination efficacy and betweenness centrality ($r_{betweenness\ centrality}$= 0.472; [LL: 0,470;UL:0.473]). Such measure, as described by Zhang et al. (2020), it is an indicator of bridging positions. However, users who often resides in the middle way of the shortest path of two other users, are those who have the highest probability to spread a product across different communities. Similarly, a positive correlation has been found between the closeness centrality and the dissemination efficacy ($r_{closeness\ centrality}$ = 0.43; [LL:0,418;UL:0.456]). It indicates that users with the shortest distance to other users, on average, tend to be more influential in spreading a recommendation across the entire network. Finally, the positive correlation between PageRank and dissemination efficacy ($r_{PageRank}$ = 0.508; [LL:0,500;UL:0.515]) confirms a user linked to parsimonious vertex highly connected with relevant vertex is more able to spread the information across different neighbourhoods.

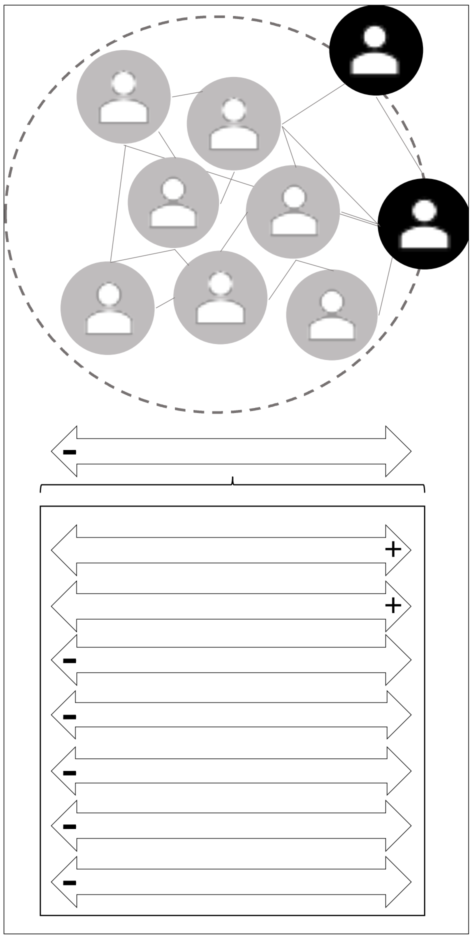


Figure 8. Dissemination efficacy according to the network measures

General discussion

In the sequence of the analysis, I discussed the implicit network of influence enabled by recommendation agents. I had argued, that such networks that aim to combine users in neighbourhoods according to their preferences, could be described as other networks investigated in the past and under the lenses of the theory of the strength of weak ties (Granovetter, 1973). I expected that users which rely on weak ties within the neighborhood are those that are more likely to convey recommendations through several neighbourhoods and to wide spread a marketing message after the purchase, whereas strong-tie consumers are more likely to mainly convey messages within their own communities. Such bridges, with a peripheral position in the community and a central role in the network, have been discussed in other studies for their ability to bring an information from the external context to the internal environment (Vikatos et al. 2020, Corradini et al. 2020, Granovetter, 1973; Burt, 1992; White, 1970). The results of the study attained similar evidences, but referring to an implicit network enabled by an algorithm. However, the network-specific analysis returned a structure composed by densely connected users but with different degrees and strengths, according to the number of times two or more users have been exposed to the same recommendation. Specifically, different strengths of the links appearing between users brought me to discover 14 significant neighbourhoods of different sizes. As observed in other social structures (Bansal and Voyer, 2000; Granovetter, 1973; Iacobucci and Hopkins, 1992; Walster et al., 1973; Brown and Reingen; 1987; Ellison and Fudenberg, 1995; Obal 2011, Ellison et al. 2007), the majority of RAs-enabled networks also highlight a densely connected center and few peripheral users within the community with a lower degree of edges. This general picture reflects the functioning of RAs which consists of measuring similarities between the users through several methods, such as Pearson correlation, mean-squared difference, k-nearest neighbour and Spearman correlation (Aggarwal, 2016, Ricci and Shapira, 2015). As an output, the similarity process returns a user similarity matrix which determines correlation/or similarities thresholds between pairs of users. According to this logic, the agency of the algorithm is pursued to an everlasting attempt to combine users with similar behaviours and recommend product accordingly. Not surprisingly, the majority of them unavoidably respond to this logic, while a minority of them is not definitively embedded. This could be mainly for three reasons: 1) such users are newcomers in the entire network and demonstrated few activities which prompted them to a marginal position of a community; (2) they are progressively demonstrating preferences that are moving them toward the neighborhood; (3) they demonstrated cross-sharing activities highlighting behaviours that could be referred to more than one community.

Regardless their status, I posited that such positions are associated to higher dissemination of the product recommendation and the results of the correlation analysis on 100 bootstrapped samples confirmed my initial hypothesis. However, embedded users which rely on a higher degree of edges with the users of their communities are those who are less incline to wide spread the message across other neighbourhoods (H2 and H2a) whereas, those who belong to a neighborhood but rely on lower degrees of embeddedness are more likely to widespread the recommendation across different neighbourhoods (H1 and H1a). Such findings, are also confirmed by the estimate of the participation coefficient, highlighting that users with lower within-community connectivity tend to disseminate more recommendations across the network. Consequently, the average closeness centrality and betweenness centrality support these results, demonstrating that those users characterized by short distance with others and often resides in the middle way of the shortest path of two other users are more likely to spread the recommendation. These two measures, under conditions of the existence of neighbourhoods document that those who are highly embedded in a community cannot rely on central positions of the main network since their connections mainly refer to the members of the community itself, which is a subnetwork of the main structure. Conversely, those who share links with members of different communities, tie with a large numbers of users disseminated in the network. Also, these condition is significantly altered according to the eigenvector centrality which returns a second layer of dissemination power in consonance with the quality of the connection with the most connected vertex of a community. This observation raises an evidence that under these circumstances weak-tie users connected with popular vertices are more influential even of generic weak-tie users. It is confirmed by the higher estimate of the eigenvector centrality obtained in the analysis. As I noted, the PageRank measure supports these evidences resulting in the second highest coefficient of the analysis and describing that connection with relevant vertices increase the recommendation dissemination.

More generally, the findings suggest that RAs implicit networks are composed by different users neighbourhoods which rely on a gradient of recommendation dissemination that varies according to the embeddedness of the users in a community, the centrality and connections with relevant other users of a neighborhood. Those who are less connected in a community, widespread the information across different neighborhood, while highly-connected users tend to spread the recommendation in their community. It means that, well-connected members of a community are more likely to deliver the communication only within the community, while weak-ties users to reach their neighborhood and the others.

Practical implications

The findings raises some practical implications for those marketers hoping to increase the dissemination of product recommendations along an e-commerce platform. However, through the use of RAs they should pay close attention to the nature of the network where they are putting the communication and different role of the users. This lead to conceive the targeting process differently recognizing that users are associated to different degrees of recommendation dissemination and the could be targeted accordingly. In fact, prompting users with bridge roles toward the purchase of a product would activate, exploiting the neighborhood-based collaborative filtering functioning, a recommendation toward thousands of users and several neighbourhoods. This could be a beneficial targeting process for marketers that allow to activate one user to target thousands of them. The required condition to initiate this process is the purchase from the bridge user appearing in the network that could be triggered with a sequence of incentives or promotions. As a consequence, the product bought will be automatically recommended to other users. This implication, also allows to reduce costs associated to a marketing campaign. While the relevance of influencer marketing has been discussed with regards to social networks (Dost et al., 2019), considering the findings of the present study, marketers should be aware of the existence of neighbourhoods within e-commerce platforms also and the different roles of users.

However, one of the main shortcomings that could face marketers regards the identification of such users. In recent years, some advances have been promoted in other contexts to define a set of measures that could allow practitioners to find users with a bridge positions. For instance, Vikatos et al. (2020) discussed the application of bridge-extractions algorithms on Twitter and Foursquare and proposed a sequence of measures which allow to define the bridge participation, i.e. an influence metric based on the peripheral positions of that users that are in the middle of the path between the own network and the other. This evidence lead to some implications also for e-tailers which convey product recommendations according to the RAs. Indeed, allowing brands to refine the choice about the users to target while describing their role in the community and providing automated method of bridge-extraction, could (1) benefit those with bridge position increasing their likelihood to get promotions or discounts and the overall experience within the platform; (2) favoring different options to sellers for the targeting strategies they want implement and allowing them to have more control on the output; (3) widen the e-tailers' business models through the definition of different pricing tiers according to the targeting process pursued by the marketer.

Beyond these practical implications, the findings have theoretical implications for research on communities, product recommendation and advice taking.

Theoretical implications and further research

This article has a number of limitations which present opportunities for future research. First, I based the analysis on a public Amazon's dataset of 2018 without considering sociodemographic differences among the users. Also, future researches could discover whether neighbourhoods vary over the time and users with bridge positions maintain their roles or are progressively embedded within the communities. Second, I present evidences based on the gift cards sold by Amazon, but there are still further questions concerning the type of product involvement. Indeed, as shown by several authors, RSs change their effects based on the product being offered (Senecal, 2002; Senecal and Nantel 2005, Fasolo et al., 2005) and substantial differences in the ties degrees could be assessed with regard to low-involvement vs. high involvement products (Clarke and Belk 1978, Engel and Blackwell 1982). Third, I focused on the dissemination of recommendations without considering the conversion rate of the product recommended. This is an area of investigation that could potentially help answer questions about the effectiveness of such algorithmic recommendations to prompt users toward the purchase. Forth, this research observed the results of users' behaviours without explaining their antecedents.

However, prior literature of recommendation agents mainly focused on the effects of such agents on consumer-decision making process (Resnick and Varian, 1997; Haubl and Murray, 2006; Haubl and Trifts, 2000; Swaminathan, 2003; Pedersen, 2000; Senecal et al., 2005; Senecal, 2004; Sinha and Swearingen, 2001) and the implied computational methods (Aggarwal 2016; Ricci, 2015)), whereas previous research has not explored the ability of RAs to generate implicit networks, their structures and the role of users within them. The research represents the first contribute which discuss the implicit network of influence and the role of users within them. While other studies focused on how weak ties favour the flow of information in physical contexts, I investigated such conditions in a RAs-enabled ties and networks. The findings suggest that the weak ties, with a peripheral position in the neighborhood, are more likely to disseminate marketing messages also in RAs-enabled contexts whereas the strong ties are more incline to communicate within their communities.

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Appendix 1. Script

#Dataset pre-processing in Python

In [ ]:

```
# Imports
import os
import json
import gzip
import pandas as pd
from urllib.request import urlopen
import numpy as np
```

In [ ]:

```
#Get "also buy" recommendation

metadata = pd.read_json('meta_Gift_Cards.json',lines=True)
metadata.head()

metadata = metadata[['also_buy','asin']]

metadata_object = []

for index, row in metadata.iterrows():
    new_object = {"asin":"", "also_buy":""}
    new_object["asin"] = row["asin"]
    new_object["also_buy"] = row["also_buy"]
    new_object["also_buy"].sort()
    metadata_object.append(new_object)
```

In [ ]:

```
#Append recommendation to ASINs

all_arrays = []

for row in metadata_object:
    all_arrays.append(row["also_buy"])



xt = np.concatenate(all_arrays)
asin_univoci = list(set(xt))
```

In [ ]:

```
#Get Reviewers/Shopper and associated ASIN
reviews = pd.read_json('Gift_Cards.json',lines=True)

reviews = reviews[['reviewerID','asin']]

reviews.head()

len(reviews)

reviewers_oggetto = []
```

```
for index, row in reviews.iterrows():
    new_object = {"asin":"", "reviewerID":""}
    new_object["asin"] = row["asin"]
    new_object["reviewerID"] = row["reviewerID"]
    reviewers_oggetto.append(new_object)
```

In [ ]:

```
# Unique reviewers
all_reviewers = []

for row in reviewers_oggetto:
    all_reviewers.append(row["reviewerID"])

reviewer_univoci = list(set(all_reviewers))

df = pd.DataFrame(0, columns = asin_univoci, index=reviewer_univoci, dtype=object)
```

In [ ]:

```
#Match Reviewers/Shopper and recommendation received

for review in reviewers_oggetto:
    asin_da_trovare = review["asin"]

    found_product = {}
    for x in metadata_object:
        if x["asin"] == asin_da_trovare:
            found_product = x
            break
        else:
            x = None

    for product in found_product["also_buy"]:

        df.at[review["reviewerID"],product] =  df.at[review["reviewerID"],product] + 1
        print(review["reviewerID"], product)
        print("\n")
```

In [ ]:

```
#Data analysis in R
```

In [ ]:

```
# Libraries
library(igraph)
library(sna)
require(ape)
library(NetworkToolbox)
library(bipartite)
library(dnet)
library(bigalgebra)
```

In [ ]:

```
#load initial edgelist
network_csv <- read.csv("alllines.csv", header=FALSE)
```

In [ ]:

```
#Graph based on edglist + df removal
network_graph <- graph.data.frame(network_csv, directed=T)
rm(network_csv)
```

In [ ]:

```
#Bipartite Graph User*Recommended item
V(network_graph)$type <- bipartite_mapping(network_graph)$type # Two-mode graph
V(network_graph)$color <- ifelse(V(network_graph)$type, "lightblue", "salmon")
V(network_graph)$shape <- ifelse(V(network_graph)$type, "circle", "square")
E(network_graph)$color <- "lightgray"
V(network_graph)$size <- 10
```

In [ ]:

```
#Incidence matrix - User-product
personproduct_matrix1 <- as_incidence_matrix(network_graph)
colnames(personproduct_matrix1) <- gsub(' ','',colnames(personproduct_matrix1))
```

In [ ]:

```
#remove unused dfs
rm(network_graph)
```

In [ ]:

```
# Adjacency matrix user*user + links within the cells
person_person_matrix <- (personproduct_matrix) %*% t(personproduct_matrix)
diag(person_person_matrix) <- 0
```

In [ ]:

```
# User*User graph
person_person_graph1 <- graph_from_adjacency_matrix(person_person_matrix,
mode="undirected", weighted = TRUE)
# Removal of isolated elements
Isolated = which(igraph::degree(person_person_graph1)==0)
person_person_graph <- igraph::delete.vertices(person_person_graph1, Isolated)
```

In [ ]:

```
rm(person_person_graph1)
```

In [ ]:

```
# Graph measures
#diameter is the length of the longest path (in number of edges) between two nodes
diameter(person_person_graph, directed=FALSE, weights=NA)
```

In [ ]:

```
#mean_distance is the average number of edges between any two nodes in the
network
mean_distance(person_person_graph, directed=FALSE)
```

In [ ]:

```
#edge_density is the proportion of edges in the network over all possible edges that
could exist
edge_density(person_person_graph)
```

In [ ]:

```
#reciprocity measures the propensity of each edge to be a mutual edge; that is, the
probability that if i is connected to j, j is also connected to i.
reciprocity(person_person_graph)
```

In [ ]:

#transitivity, also known as clustering coefficient, measures that probability that adjacent nodes of a network are connected. In other words, if i is connected to j, and j is connected to k, what is the probability that i is also connected to k?
igraph::transitivity(person_person_graph, type="global")

In [ ]:

#degree, the number of adjacent edges to each node. It is often considered a measure of direct influence.
mean(igraph::degree(person_person_graph))

In [ ]:

#Strength is a weighted measure of degree that takes into account the number of edges that go from one node to another. In this network, it will be the total number of interactions of each character with anybody else.
mean(igraph::strength(person_person_graph))

In [ ]:

#Closeness measures how many steps are required to access every other node from a given node. It's a measure of how long information takes to arrive (who hears news first?). Higher values mean less centrality.
mean(igraph::closeness(person_person_graph))

In [ ]:

#Betweenness measures brokerage or gatekeeping potential. It is (approximately) the number of shortest paths between nodes that pass through a particular node.
mean(igraph::betweenness(person_person_graph))

In [ ]:

#participation coefficient
min(participation(person_person_matrix, comm = c("walktrap", "louvain"))$overall)
max(participation(person_person_matrix, comm = c("walktrap", "louvain"))$overall)
mean(participation(person_person_matrix, comm = c("walktrap", "louvain"))$overall)

In [ ]:

#degree distribution and vertex and edges count
ecount(person_person_graph)
vcount(person_person_graph)

In [ ]:

#community detection
kc <- multilevel.community(person_person_graph)

In [ ]:

#size of community detected
sizes(kc)

In [ ]:

 # modularity
modularity(kc)

In [ ]:

#Wilcoxon t-test
dCommSignif(person_person_graph,comm = kc)

In [ ]:

 # density network vs density neighborhood
graph.density(person_person_graph)

In [ ]:

#density communities
for (index in 1:length(kc)){

```
  ego.admin <- induced.subgraph(graph=person_person_graph, kc[[index]])
  print(graph.density(ego.admin))
  print(index)
}
```

In [ ]:

```
#nodes measures
persons_with_measures <- matrix(nrow = nrow(person_person_matrix), ncol = 9)
rownames(persons_with_measures) <- rownames(person_person_matrix)
colnames(persons_with_measures) <- c('EigenCentrality', 'Embeddedness (Transitivity)',
'ParticipationCoefficient', 'DegreeCentrality', 'ClosenessCentrality', "Authority",
"BetweennessCentrality","PageRank", "DiffusionPower")
```

In [ ]:

```
# eigencentrality
persons_with_measures[,'EigenCentrality'] <- eigen_centrality(person_person_graph,
directed = FALSE, weights = NULL, options = arpack_defaults)$vector
```

In [ ]:

```
#closeness centrality
persons_with_measures[,'ClosenessCentrality'] <-
igraph::estimate_closeness(person_person_graph, mode = "all", cutoff=1)[1000:3000]
```

In [ ]:

```
# embeddedness
persons_with_measures[,'Embeddedness (Transitivity)'] <-
igraph::transitivity(person_person_graph, type='local')[1:2000]
```

In [ ]:

```
# participation coefficient
persons_with_measures[,'ParticipationCoefficient'] <- participation(person_person_matrix,
comm = c("walktrap", "louvain"))$overall
```

In [ ]:

```
# degree centrality
persons_with_measures[,'DegreeCentrality'] <- centr_degree(person_person_graph)$res
```

In [ ]:

```
#authority
persons_with_measures[,'Authority'] <-authority_score(person_person_graph)$vector
```

In [ ]:

```
#betweeness centrality
persons_with_measures[,'BetweennessCentrality'] <-
igraph::estimate_betweenness(person_person_graph,directed = FALSE,
cutoff=2)[1000:2000]
```

In [ ]:

```
#Page Rank
persons_with_measures[,'PageRank'] <- page_rank(person_person_graph)$vector
```

In [ ]:

```
#Definition of recommendation diffusion indicator
```

In [ ]:

```
#Cluster*Sum of recommended products Matrix
cluster_product <- matrix(0L, nrow = length(kc), ncol = ncol(personproduct_matrix))
colnames(cluster_product) <- colnames(personproduct_matrix)
```

```
for (cluster_index in 1:length(kc)) {


  for (person in 1:length(kc[[cluster_index]])) {

    cluster_product[cluster_index,] <- array(cluster_product[cluster_index,]) +
array(personproduct_matrix[person,])

  }

}
```

In [ ]:

#Recommended products to a cluster

```
cluster_product[cluster_product==0] <- NA
```

In [ ]:

#Products bought by each individual

```
product_purchases_matrix <- read.csv("acquisti.csv", row.names = 1)
product_purchases_matrix <- as.matrix(product_purchases_matrix)
cluster_product_purchase <- matrix(0L, nrow = length(kc), ncol =
ncol(product_purchases_matrix))
colnames(cluster_product_purchase) <- colnames(product_purchases_matrix)
```

In [ ]:

```
for (cluster_index in 1:length(kc)) {


  for (person in 1:length(kc[[cluster_index]])) {

    cluster_product_purchase[cluster_index,] <-
array(cluster_product_purchase[cluster_index,]) +
array(product_purchases_matrix[person,])

  }

}
```

In [ ]:

#Count of product bought by each individual in the cluster

In [ ]:

```
cluster_product_purchase[cluster_product_purchase==0] <- NA
```

In [ ]:

```
reccommended_buy_matrix <- matrix(0L, nrow = length(kc), ncol =
ncol(product_purchases_matrix))
colnames(cluster_product_purchase) <- colnames(product_purchases_matrix)

for (row in 1:nrow(cluster_product)) {
  for(column in 1:ncol(cluster_product)) {
    if(is.na(cluster_product[row, column]) == FALSE &&
is.na(cluster_product_purchase[row, column]) == FALSE) {
      if (cluster_product[row, column] > 0 && cluster_product_purchase[row, column] > 0)
{
```

```
        reccommended_buy_matrix[row, column] <- cluster_product[row, column]
      }
    }

  }

}
```

In [ ]:

#Count how many times a product has been purchased in a cluster

```
reccommended_buy_matrix[reccommended_buy_matrix==0] <- NA
```

In [ ]:

```
product_cluster_matrix_diffusion <- matrix(0L, nrow = nrow(person_person_matrix),
ncol = length(kc))
rownames(product_cluster_matrix_diffusion) <- rownames(person_person_matrix)
```

In [ ]:

#Matrix for recommendation diffusion - From one user to n clusters

```
for (person in rownames(product_cluster_matrix_diffusion)) {
  # prodotti acquistati dalla persona
  purchases <- colnames(product_purchases_matrix)[product_purchases_matrix[person,] >
0]

  for (purchase in purchases) {
    for (cluster_index in 1:length(kc)) {
      #print(cluster_product[cluster_index,][purchase])
      if (is.na(cluster_product[cluster_index,][purchase]) != T) {
        #print(purchase)
        product_cluster_matrix_diffusion[person,cluster_index] <- 1
      }
    }
  }
}
```

In [ ]:

#Attach to matrix

```
product_cluster_matrix_diffusion[product_cluster_matrix_diffusion==0] <- NA
#rowMeans(product_cluster_matrix_diffusion, na.rm = TRUE)
#rowSums(product_cluster_matrix_diffusion, na.rm = TRUE)
colnames(product_purchases_matrix)[is.na(product_purchases_matrix) == FALSE]
colnames(product_purchases_matrix)
colnames(product_cluster_matrix_diffusion)
persons_with_measures[,'DiffusionPower'] <-
rowSums(product_cluster_matrix_diffusion,na.rm = TRUE)
```

In [ ]:

```
if(!require(psych)){install.packages("psych")}
if(!require(PerformanceAnalytics)){install.packages("PerformanceAnalytics")}
if(!require(ggplot2)){install.packages("ggplot2")}
if(!require(rcompanion)){install.packages("rcompanion")}
```

In [ ]:

#correlation among values per matrix

```
corr.test(persons_with_measures,
```

```
        use    = "pairwise",
        method = "pearson",
        adjust = "none")
```

In [ ]:

#Iterate 100 correlation matrices (with n=1000) using RMarkdown and get a report

```
library(knitr)
library(markdown)
library(rmarkdown)
library(stringr)

subsample <- c(1:100)

for(i in 1:length(subsample)){
  rmarkdown::render(
    input = "NetworkAnalysis-Markdown.Rmd",
    output_file = NULL,
    params = list(subsample  = subsample[i]))
}
```

In [ ]:

#Correlation table in APA format

```
apa.cor.table(persons_with_measures, filename = paste0("Report_",Sys.time(),".rtf"))
```

In [ ]:

#All correlation tables have been combined through Excel and then processed in R again

In [ ]:

```
dataset <- read_excel("~/RTF/Coefficientsestimates.xlsx")
```

In [ ]:

#plot correlation coefficients distribution

```
hist(dataset$`1. EigenCentrality`, col="white", border="black", main="EigenCentrality
Coefficient Distribution", font.lab=2, xlab="r EigenCentrality")
abline(v=mean(dataset$`1. EigenCentrality`),col="black",  lwd=3, lty=2)
mean(dataset$`1. EigenCentrality`)

hist(dataset$'2. Embeddedness', col="white", border="black", main="Embeddedness
Coefficient Distribution", font.lab=2, xlab="r Embeddedness")
abline(v=mean(dataset$`2. Embeddedness`),col="black",  lwd=3, lty=2)
mean(dataset$'2. Embeddedness')

hist(dataset$'3. ParticipationCoefficient', col="white", border="black",
main="Participation Coefficient Coefficient Distribution", font.lab=2, xlab="r
Participation Coefficient" )
abline(v=mean(dataset$`3. ParticipationCoefficient`),col="black",  lwd=3, lty=2)
mean(dataset$'3. ParticipationCoefficient')

hist(dataset$'4. DegreeCentrality', col="white", border="black", main="Degree centrality
Coefficient Distribution", font.lab=2, xlab="r Degree centrality")
abline(v=mean(dataset$`4. DegreeCentrality`),col="black",  lwd=3, lty=2)
```

```
mean(dataset$'4. DegreeCentrality')

hist(dataset$'5. ClosenessCentrality', col="white", border="black", main="Closeness
Centrality Coefficient Distribution", font.lab=2, xlab="r Closeness Centrality ")
abline(v=mean(dataset$`5. ClosenessCentrality`),col="black",  lwd=3, lty=2)
mean(dataset$'5. ClosenessCentrality')

hist(dataset$'6. BetweennessCentrality', col="white", border="black", main="Betweenness
Centrality Coefficient Distribution", font.lab=2, xlab="r Betweenness Centrality")
abline(v=mean(dataset$`7. BetweennessCentrality`),col="black",  lwd=3, lty=2)
mean(dataset$'6. BetweennessCentrality')

hist(dataset$'7. PageRank', col="white", border="black", main="PageRank Coefficient
Distribution", font.lab=2, xlab="r PageRank ")
abline(v=mean(dataset$`8. PageRank`),col="black",  lwd=3, lty=2)
mean(dataset$'7. PageRank')
```

In [ ]:

```
#ANOVAs after Fisher's transformation
model <- aov(dataset$'Z-EigenCentrality'~dataset$'Sample', dataset)
model1 <- aov(dataset$'Z-Embeddedness'~dataset$'Sample', dataset)
model2 <- aov(dataset$'Z- ParticipationCoefficient'~dataset$'Sample', dataset)
model3 <- aov(dataset$'Z- DegreeCentrality'~dataset$'Sample', dataset)
model4 <- aov(dataset$'Z- ClosenessCentrality'~dataset$'Sample', dataset)
model5 <- aov(dataset$'Z-Authority'~dataset$'Sample', dataset)
model6 <- aov(dataset$'Z- BetweennessCentrality'~dataset$'Sample', dataset)
model7 <- aov(dataset$'Z- PageRank'~dataset$'Sample', dataset)
```

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Chapter III. When the Fit is Too Tight: Unveiling the Effects of Unlearning and Novelty to Counteract the Algorithms Overspecialization

Abstract

Users nowadays rely on the efforts of recommendation agents (RAs) that build customised experiences according to user's preferences. While designed to help users in their purchase decision processes, RAs ultimately lead to a reinforcement of people's existing preferences as they typically recommend users to buy products that are in line with their inferred preferences, thus limiting the possibility that a consumer might consider options that do not match their interests (i.e., overspecialization). In the investigation, I move from the idea that higher degrees of RAs specialization confines users within their preferences and negatively affect the choice outcomes. In a sequence of four studies and a sample of 1325 online users, I investigate the effects of RAs specialization on users' choice outcomes, their antecedents and a potential solution to the issue. Study 1 investigates how increasing levels of RAs specialization reduce the users' outcomes. Study 2 sheds light on the antecedents of the acceptance/rejection of overspecialization by assessing the perceived reciprocity and intimacy conveyed by generalised and specialised RAs. Study 3 assesses the specialization as a factor that may reduce the formation of new preferences and negatively affects the breadth of users' knowledge and, subsequently, the users outcomes. Finally, study 4 evaluates the effectiveness of algorithmic novelty as a way to counteract RAs specialization and the decrease of choice outcomes. The findings contribute to the advice-taking literature proving that the users do not necessarily use RAs to get recommendations in line with their preferences but also to expand their preferences. From a managerial perspective, this research suggests to adapt RAs to a follower approach to create the right combination of rated and novel products.

Keywords – Recommendation Agents; Overspecialization; Novelty; Reciprocity; Intimacy; Breadth of Knowledge; Depth of Knowledge; Algorithms

Paper type – Research Article

Introduction

The advent of the internet and postmodernism have overturned the consumption habits by reassembling the established offline practices in new online marketplaces (Wichmann et al., 2022). An all-encompassing shift that prompted the bulk of markets towards a new context characterised by the coexistence of online, offline or even hybrid stores. Nowadays, the value generated by such online marketplaces accounts for $26.7 trillion (Unctad, 2021).

The ensuing proliferation of online players in such refashioned setting has also benefited users with a larger selection of products, lower prices and customised journeys (Li et al., 2021). Online platforms as Amazon, Booking.com, Spotify and Zalando, offer thousands of items while minimising the search costs and the risk of making an unsatisfying decision in largely assorted marketplaces (Hamilton et al, 2021). This is made possible and fostered by Recommendation Agents (RAs) which collect the preferences of users and recommend items accordingly (Longoni et al., 2022; Liu-Thompkins et al., 2022; Lim et al., 2022; Xie et al., 2022; Banker et al., 2019; Henning-Thurau et al., 2012; Fitzsimons et al., 2004). The domain of RAs is very broad and spans from the Google PageRank (Page et al., 1999) to the recommendation provided on marketplaces. These algorithms are embedded in e-commerce platforms and exerts their influence through statements like "You may also like…" or "People who like this also like" or altering the position of items in the webpages (Gai et al., 2019). It has been estimated that the 92% of online searches originate from a RA and a vast majority of users adopt them on a daily basis to get advices about products and services on the internet (International Data Corporation, 2019).

With technological developments that have made RAs highly accurate from a computational standpoint (Gai et al., 2019), these algorithms commonly work as substitutes of gatekeepers, experts, and possibly even decision makers as key actors involved in the purchase decision process (Lee et al. 2017), due to their ability to convey messages that are tailored to specific consumer's interests (Hamilton et al., 2021). They are particularly useful when individuals do not have a preferred option, delegate the shopping process to someone else (i.e., hybrid-decision making process) or are unaware of the entire assortment (Lee, 2018; Aggarwal et al., 2008; Senecal et al., 2005). RAs reduce search costs and support users in the identification of relevant items in a vast collection of products (Banker et al., 2019), influence users' consideration set diminishing the number of product considered (Longoni et al., 2022;

Hennig-Thurau et al., 2012), increase the decision quality and reduce decision efforts in large assorted platforms (Liu-Thompkins et al., 2022; Cloarec et al., 2022; Haubl and Trifts, 2000).

However, while designed to help users in their purchase decision processes, RAs ultimately lead to a reinforcement of people's existing preferences as they typically recommend users to buy products that are in line with their inferred preferences (i.e., accuracy improvement)(McNee et al. , 2006), thus limiting the possibility that a consumer might consider options that do not match their interests (Matz, 2021; Shen et al. 2011).

This overspecialization originates from the everlasting improvement of RAs accuracy and is associated to the implicit risk of selecting lowly satisfying alternatives just because of the fit with users' preferences (Banker et al., 2019) and avoid the discovery of new products that might be classified as far from users' preferences (Kim et al., 2021; Banker et al., 2019). An issue already known as filter bubble (Parisier, 2011), echo-chambers (Lee et al., 2011) or serendipity problem (Kim et al., 2021).

In this investigation, I move from the idea that higher degrees of RAs accuracy reduce the information overloading but increase the degree of the specialization that confines users within their preferences and negatively affect the outcomes of the choice.

While prior research on advise-taking has primarily focused on the improvement of accuracy measures as a way to increase the match between recommended items and users' preferences (Song et al., 2019; Dzyabura et al., 2019; Isufi et al., 2021; Hamedani and Kaedi, 2019; Panniello et al., 2014; Zhou et al., 2010; Ansari et al., 2000; Haübl et al., 2000; Knijnenburg et al., 2012; Lombardi et al., 2017; Tsekouras et al., 2020; Aggarwal. 2016), the effects of overspecialization on users' outcomes and their antecedents are currently under-researched. My main argument is that RAs specialization negatively affects the perceived usefulness and benefit of the recommendation set (hereinafter also cited as RS), the willingness to accept the recommendation, users' satisfaction and enjoyment (i.e., users' outcomes or choice outcomes). In my idea, such effects arise for two reasons: (1) the RAs tacit knowledge about users can lead to a lack of perceived reciprocity and intimacy; (2) RAs tailor the recommendations to users' preference (i.e., user profile) but decrease the chance to form new preferences, additional expertise and find novel products far from the *user profile* and finally decrease the choice outcomes and the effectiveness of the RA.

Also, several scholars investigated the serendipity (Bao et al., 2022; Kim et al., 2021; Niu et al., 2021; Dzyabura et al., 2019; Grange et al., 2019; De Gemmis et al., 2015) as the only solution to the overspecialization with limited attention to other important dimensions, such as novelty. It is a remarkable gap for two main reasons. First, the novelty is a underemployed concept in marketing theory and offers a way out for overspecialization since a novel item is relevant, unexpected and never rated before by users whereas the serendipity implies a set of feelings resulting from positive associations with the stimulus and is facilitated by RAs accuracy (Kim et al., 2021). In this sense, the overspecialization and increasing levels of knowledge about users can only increase the chance to generate feelings of serendipity. Second, e-tailers hardly have any control over the feelings of serendipity associated with each purchase and can only alter the novelty of a RS by increasing or diminishing the number of new items recommended. Consequently, I contend that higher degrees of novelty are associated to higher levels of choice outcomes and pose a solution to the overspecialization issue.

To fulfil these theoretically and managerially relevant gaps, in a sequence of four studies (see Figure 1) I manipulate the RAs specialization level (i.e., overspecialised vs. specialised vs. generalised (Study 1) and degree of novelty of a RS (novel-based RS vs. accurate (Study 4), assess the perceived reciprocity and intimacy of the RA (Study 2) and the effect on user's expertise (Study 3), but keeping the underlying algorithms constant.

Study 1 implies three conditions to assess how the increasing levels of RAs learning affects choice outcomes. The results, highlight that higher levels of specialization are associated to lower choice outcomes.

Studies 2 and 3 reveal the antecedents of the avoidance of overspecialization. In Study 2, I assess how the RAs learning affects the perceived reciprocity and intimacy of users – as mediators - and in turn the choice outcomes. The results show that users feel a lack of reciprocity and intimacy when RAs increase the knowledge about them.

Study 3 investigates how the effects of RAs specialization are detrimental for users due to a reduced chance to form new preferences. The results of this study indicate that RAs are associated to higher choice outcomes when favour the breadth of knowledge rather than the depth.

Finally, Study 4 involves an online experiment where I manipulate two degrees of novelty (high vs. low) and measure their effects on perceived novelty, as a mediator, and choice outcomes. Results show that algorithmic novelty (i.e., the ability of the algorithm to provide items far from users' preferences) is a viable solution to the overspecialization problem and related to higher choice outcomes.

I base my proposition on insights from knowledge transfer theory and advise-taking research. According to the knowledge transfer literature, I conceptualize RAs as tools able to tacitly observe users and provide them with recommendations in return. While advise-taking research propose a clarification on RAs algorithms and their effects.

The findings contribute to the extant body of knowledge in many ways. I are among the first to measure the effects of algorithmic overspecialization on users choice outcomes and discover the value of unlearning as a beneficial process to improve product recommendations. Also, I further explain the main antecedents of such issue and discuss the algorithmic novelty as the viable solution to the issue.

From a managerial perspective, this research suggests how to set the RAs on a follower mode, allow for unlearning, enhance the breadth of knowledge and balance the RSs with preferred and novel products.

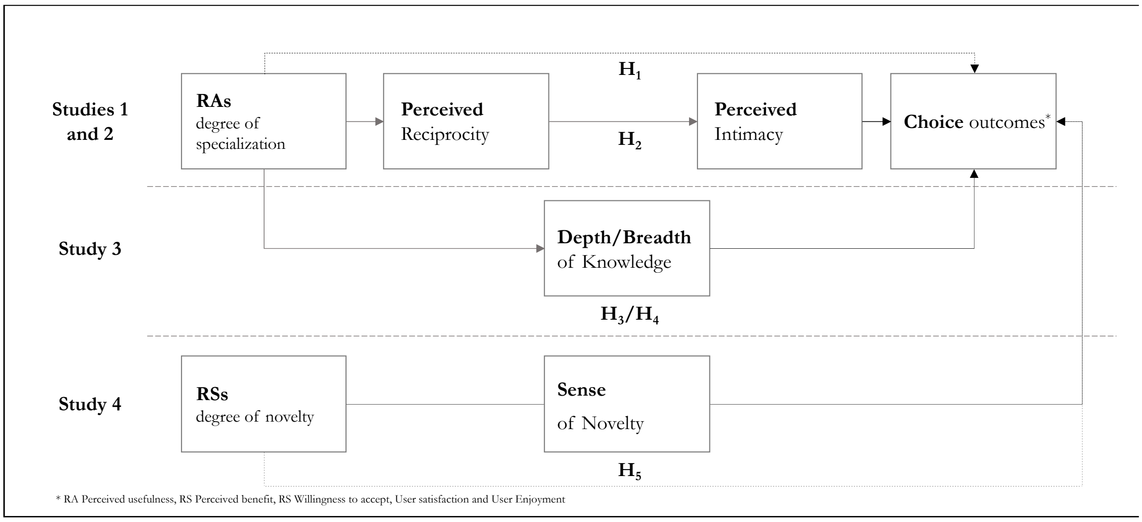

Figure 1. RAs degree of specialization and its role in online marketplaces – Conceptual model

Theoretical Background

Recommendation Agents and the overspecialization problem in online marketplaces

To counteract the Long-Tail problem and the overwhelm of information, e-tailers have introduced RAs to provide users with personalized set of items by collecting their preferences – explicitly or implicitly - (Schafer, 2007; Senecal, 2004 and 2005) and model a navigation journey tailored to their individual instances (Aggarwal, 2016; Ansari et al, 2000; Cheney-Lippold, 2011). RAs can be classified in personalized and non-personalized algorithms: such tools can either provide indistinct suggestions to all users based on generic features of the item (i.e., popularity) or depending on the user preferences (i.e., expressed rating). According to the second method, RAs need to build a *user profile* that includes behavioural and socio-demographic information of the user (Kotkov et al., 2016). It is made possible through an elicitation process that can be implicitly pursued by inferring users' preferences during their interactions with the e-tailer's ecosystem (i.e. page viewed, browsing history, products bought)(Kramer, 2007) or, explicitly, by requiring an extra-effort to the users, who are asked to provide an evaluation on the preferred items or features (such as in the Netflix account set-up phase) (Aggarwal, 2016).

IS literature has extensively investigated how to leverage the preference elicitation process to improve RAs effectiveness and build more accurate user profiles (Song et al., 2019; Dzyabura et al., 2019; Isufi et al., 2021; Hamedani and Kaedi, 2019; Panniello et al., 2014; Zhou et al., 2010; Ansari et al., 2000; Haübl et al., 2003; Knijnenburg et al., 2012; Lombardi et al., 2017; Tsekouras et al., 2020; Aggarwal. 2016). The accuracy is nowadays the main goal of RAs and refers to the ability of performing recommendations with a high fit with the preferences of the user (Ansari et al., 2000).

However, the incessant attempt to automatically improve RAs accuracy by monitoring users' actions lead to bound individuals within their existing preferences and knowledge i.e., overspecialization problem (Kim et al., 2021). As a result, users can rapidly become tired of the RS received because of (1) a lack of diverse suggestions i.e., if the main reason for utilizing a RA is to discover new products they might stop accepting the suggestions when they only offer items that are similar to those already viewed; (2) their familiarity with products they have already interacted with (Kotkov et al., 2016). This drawback can even increase the Long-Tail problem by generating a multitude of consumption niches originated around predefined preferences and lessen the chances to see new items which are not associated to the user profile (Lamberton et al., 2016; Hosangar et al., 2014).

To understand how users can benefit of generalised RAs and exposure to new products, I draw on advice-taking research and knowledge transfer theory (Bandura, 1977). The first, consider RAs as social agents able to mimic WOM recommendations leveraging on the user profile to generate suggestions about products and services (Ansari et al., 2000). Whilst, Bandura (1977) asserts that learning about unknown items, or far from our preferences, is based on a vicarious learning which allow to indirectly understand the effects of such new items without taking the risk to experience them (Hirschman, 1980). In fact, trough the observation of others' recommendations or usage, individuals expand their knowledge and experience (Bandura, 2001: 271). It is made possible from a comparison between individuals' learning resources (i.e., intelligence and imagination) with the operant (e.g., specialistic knowledge) and operand resources (e.g. information or details) manifested by external cues generated by other agents. Consequently, thanks to this interaction, individuals form their knowledge structure and, thus, learn in a vicarious way from the observation of other agents' usage or recommendations about new items (Hibbert et al., 2012).

Such interactions lead individuals to imagine the novel products and their applications (Schifferstein, 2016; Desmet and Hekkert, 2007), build mental norms and procedures for elaborating information about the new items (Hollebeek et al., 2016; Sinkula et al., 1997) and develop expectations prior to their use (Wood and Moreau, 2006). This process, results in a modification of individual's preferences and behaviour in light of the new knowledge generated (Hollebeek et al., 2016).

Prior research has also confirmed that users when exposed to humans recommendations, adjust their preferences for unfamiliar products and found that RSs based on items far from existing preferences are associated to higher levels of enjoyment, satisfaction and more positive attitudes and higher levels of satisfaction (Morvinski, Amir, and Muller 2017; Yaniv, Choshen-Hillel, and Milyavsky 2011, Hilmert, Kulik, and Christenfeld 2006; Naylor, Lamberton, and Norton 2011). Other authors, proposed a solution to the overspecialization problem by writing algorithms which find hidden correlations among items and increase the level of serendipity (De Gemmis et al., 2015).

To the best of my knowledge, no research in marketing has suggested the effects of overspecialization on the perceived usefulness of the RA and perceived benefit of the RS, the willingness to accept the recommendation, users' satisfaction and enjoyment. Consonant with the previous argumentation, I contend that RAs are adopted by users to inform their preferences and generalised RAs, with lower degrees of specialization, are perceived as more enjoyable, satisfying, useful and are more accepted by users because of their ability to expose them to nurture new preferences. Studied 1 and 4 are combined in a cause-and-effect relationship. Study 1 is meant to explore the outcomes associated to increasing levels of knowledge of RAs (i.e., the cause) while the Study 4 to observe the output of the knowledge, a novel or an accurate RS (i.e., the effect). Therefore, I formally hypothesise that:

H_1: Higher degrees of RAs specialization negatively affects choice's outcomes, such that the perceived usefulness and benefit of the RS, the willingness to accept the recommendation, users' satisfaction and enjoyment are lower than in the presence of generalised RAs

The RAs tacit knowledge

Almost three decades ago, the chess champion Garry Kasparov lost a match with an algorithm called Deep Blue (IBM, 1997). The defeat shocked the entire world and perceptually opened to a new era of artificial intelligence. However, it seems that a few years ago, Kasparov made his peace with the algorithm thanks to a new beneficial sequence of interactions that helped both to learn and generate new knowledge (Knight, 2020).

Indeed, in the human-agents interactions, there is an hidden currency that is always exchanged – often implicitly – which is the tacit knowledge (De Bruyn et al., 2020). It is transferred through observation, imitation, and practice (Nonaka, 1994, p. 19; Bandura, 1977). When interacting with online marketplaces, users provides their information that are transformed in tacit knowledge by RAs which in turn, utilize them to generate RSs. An exchange that would benefit users if it mutually increase the knowledge of each other (De Bruyn et al., 2020; Nonaka, 1994). However, in this interactions, only RAs acquire information whilst users receive in return a RS (De Bruyn et al., 2020). This RS is computed with the constant aim to maximize the accuracy which lead to the issue of overspecialization (Castelo et al., 2019). A problem that does not allow to offer new knowledge to users since the algorithm attempts to create a suit with best fit with the users without giving the chance to try items far from his/her preferences (Kim et al., 2021). An interchange that does not allow user to distance themselves from the user profile. This drawback negatively impacts users, since they won't discover items far from their preferences and online retailers because of the absence of information about items deemed incongruent (Kim et al., 2021).

Prior research has demonstrated that users acceptance of targeted recommendations is mediated by the reciprocity, an accepted societal rule requiring individuals to give back part of the benefits earned (Schumann et al., 2014; Gouldner, 1960). *"The norm of reciprocity is clearly motivational; it provokes a person's innate desire to repay a favor, typically driven by a feeling of indebtedness"* (Greenberg 1980). Such norm, affects user's acceptance of messages in return for the service provided by the retailer. Contrarily, users negatively react to information source which are not perceived as engaged in reciprocal behaviours and act unobserved and anonymously (Schumann et al., 2014). It implies a low likelihood of favourable outcomes if one actor of the relationship doesn't reciprocate (Sprecher et al., 2013). When the other shares knowledge or information, people tend to be more connected (Collins and Miller, 1994). Reciprocity makes the RA more authentic and stimulates the development of intimacy and trust (Becker and Mark, 1999). The intimacy, in turn, is affected by reciprocity and the perception of user about the RAs self-disclosure (Laurenceau et al., 2005). When users feel the RA as a friend, close to them, able to select items for them or a general sense of familiarity, they develop a greater willingness to accept the recommendation, enjoyment, satisfaction and perceived utility of the set (Lee et al., 2017; Laurenceau et al., 2005; Reeves et al., 1996).

Accordingly, I contend that RAs are seen as tools unable to reciprocate, that tacitly derives users' preferences without giving the chance to expand their preferences. Consequently, I posit that higher levels of RAs specialization are associate to lower choice outcomes and are mediated by reciprocity and intimacy. Overspecialization lead RAs to be perceived as less reciprocal and as a consequence less intimate. A sequence of effects that negatively affects users' acceptance of RS in online marketplaces. Recapping the preceding discussion, I hypothesize the following:

H_2: Reciprocity and intimacy mediates the effects of RAs specialization on choice outcomes

The effects RAs learning on the breadth and depth of knowledge

A relevant factor that has been proved to influence the formation of new preferences is the individual product expertise (Moreau et al., 2001; Alba and Hutchinson 1987; Bettman, Johnson, and Payne 1991; Gregan-Paxton and John 1997). Indeed, the expertise affects the cognitive efforts made to assess novel products, the overall comprehension and perceptions (Moreau et al., 2001; Gatignon and Robertson 1985) and it is formed through a three-step process: the access, mapping and transfer (Gentner 1989; Holyoak et al., 1989). When individuals are exposed to novel products i.e., the access stage, they tend to map and compare such items with the primary base domain of knowledge (i.e., the existing knowledge) (Gregan-Paxton et al., 1997). Then, through the interaction they classify the new product or its features in new or existing categories and form new knowledge (i.e., transfer). Similar to Bandura's vicarious learning (1977) and Nonaka's transfer of tacit knowledge (1994), the authors who have discussed the role of knowledge in expertise formation (Moreau et al., 2001; Alba and Hutchinson 1987; Bettman, Johnson, and Payne 1991; Gregan-Paxton and John 1997) assert that the exposition to novel stimuli and the interaction with previous knowledge allow consumers to form expertise and new preferences.

In context mediated by recommendations, two types of knowledge contributes to the formation of expertise: the breadth and depth of knowledge (D'Angelo and Valsesia, 2022). While depth refers to an in-depth knowledge of each specific alternative, breadth refers to the comprehensive knowledge of all the possibilities within a category (Clarkson, Janiszewski, and Cinelli, 2013; Manucci and Yong, 2018; Yang, Jin, and Sheng 2016). When forming new expertise about products, consumers tend to leverage on the breadth to form the depth knowledge (D'Angelo and Valsesia, 2022). As a result, the greater is the number of items proposed, the higher the alternatives to compare to form new knowledge and preferences.

However, consumers do not exclusively rely on their own expertise but can infer their decisions by leveraging on others' expertise and knowledge (Sela, 2019; D'Angelo and Valsesia, 2022). In RAs-mediated context, the algorithm has its own expertise and can be differently perceived by users. Recent research (D'Angelo and Valsesia, 2022; Sela, 2019), proved that when consumers assess the level of expertise of external agents, look for cues that signal if the other has a depth or breadth knowledge. They have demonstrated that recommendation agents are viewed as expert since they signal greater breadth of knowledge when recommend diverse product whilst the perception of depth increase when they are focused on the same product category (D'Angelo and Valsesia, 2022).

Accordingly, Banker et al., (2019) determined that when expert and non-expert individuals of a product category adopt expert or non-expert RAs to select items leverage on both RAs breadth and depth of knowledge. Indeed, non-expert users when interact with expert algorithms, tend to select the product recommended (i.e., depth, in line with their preferences) in 76% of cases and other products (i.e., breadth, not aligned to users preferences) in 24%; whilst when the algorithm has lower expertise, users select other product in the 50% of cases. As for users with high expertise, when the RA has high expertise they select the others (50%) and recommended items (50%) in the same percentage whilst, when the RA has low expertise, they select the recommended items in 64% of cases and others products in 36% (Banker et al., 2019). In their work, the authors showed when users use RAs for their decisions even if the recommended option is not a superior choice. An additional relevant point in this study, is the number of individuals that selected products not aligned to users preferences: in two conditions out of four, users selected diverse options in 50% of cases whereas in the remaining two conditions, more than one third of users selected diverse options. An evidence that need further investigations, since authors properly highlighted how many times users selected non-recommended alternatives without explaining the reasons and the effects of this selection on choice's outcomes. Moreover, it is not clear wheater users reputed the level of specialization as beneficial or detrimental after the selection and the drivers that can explain such relevant number of users that selected diverse option. This consistent selection of diverse products it's a relevant research outcome that deserves further consideration and if manipulated in a study can lead to different evaluations of the RA.

Drawing on these findings, I contend that users adopt RAs even to form their preferences and not only to find product related to them. Overspecialized algorithms limit their chances to enhance the breadth of knowledge and acquire new expertise, regardless they are expert or non-expert.

Formally,

H_3: The effect of RAs specialization on choice outcomes is mediated by the enhancement of the breadth and depth of knowledge

H_4: Generalised RAs are associated to higher levels of breadth of knowledge and choice outcomes

Novelty in Recommendation Agents

Prior research has defined novelty as the degree to which a response is "evaluated as new, original, and different," (Massetti, 1996, p. 87) or as a combination between a lack of familiarity and previous experience (Yim et al., 2017). It can be generated by different stimuli such as products, specific features or positions (Forster et al., 2009). In online marketplaces, the novelty concerns items that have been recently introduced, never purchased or rated by the user (De Gemmis et al., 2015; McNee et al. 2006). From a computational standpoint, it is derived as the inverse of an item's popularity: the lower the number of ratings associated to an item and the higher the degree of novelty associated to it (McNee et al. 2006).

In IS domain, some scholars have discussed the novelty with limited attention to the effects on choice's outcomes. For instance, Castells et al. 2011, Vargas and Castells 2011, Adamopoulos and Tuzhilin 2014, have proposed some algorithms to compute the novelty inside RAs. Matt et al., 2014 by focusing on the perceived preference fit, discovered that it is negatively affected by novelty i.e., algorithms that recommend novel items are perceived as less able to match user's preferences. However, the valence of this perception has not been deepened. Authors in other domains found that unexpected products results in higher brand recall and more favourable brand attitude (Vashisht, 2021) and are preferred by individuals more than usual ones (Liu et al., 2020). Yim et al. (2017) studied the effectiveness of augmented reality (AR) in creating novelty and pointed out that communication supported by AR generates greater novelty. Other research, discussed the diversity measure and described novelty as a metric to assess RAs (Ziegler et al., 2005; Zhouet al. 2010)

Conversely, the extant literature has mainly focused on serendipity as viable solution to accuracy without emphasising the novelty (Bao et al., 2022; Kim et al., 2021; Niu et al., 2021; Dzyabura et al., 2019; Grange et al., 2019; De Gemmis et al., 2015; Loeb et al., 2011). A serendipitous recommendation is a novel item (i.e., unknown) which generates a feeling of surprise. Serendipity feelings arise as a consequence of positive associations, unexpectedness and the involvement of chance and generates a sense of surprise (Kim et al., 2021; Reisenzein et al., 2019). In this perspective, "a consumer listening to a music streaming service and a song he/she loves come across" (Kim et al., 2021, pp. 141) can experience feelings of serendipity. Thus, serendipitous feelings can even arise in conditions of familiar stimulus (i.e., the song in our memories that I are listening to after many years). However, it may be argued that e-tailers can hardly influence the feelings of serendipity that spans from individual's memories, perception and associations and, due to its nature, the serendipity can be even helped by overspecialization thanks to the additional knowledge generated about the users. Even a minimum detachment with the user profile will negatively affect the knowledge of his/her inner world while a deep knowledge of users will increase the chance to create as strong connection with them and understand from what kind of individual's memories, perception and associations comes the feeling of serendipity. In this perspective, serendipity does not offer a real solution to the overspecialization issue as the unknown.

Moreover, as proved by Flavel and Wellman (1977), humans tend to positively react to novel stimuli even from the infant stage of their lives and prefer them to predictable ones. It happens since a novel stimulation disrupts individuals' attention, increase the sense of novelty and, in turn, the associated outcomes towards the recommendation. When stimulus are not associate to existing shortcuts or knowledge – i.e., an existing route – new mental processes are activated to categorise the input (Reisenzein et al., 1996). As a result, individuals focus more on novel items while predictable cues lead to an inferior attention and arousal (Easterbrook 1959).

In online marketplaces, even highly accurate recommendations (i.e., resulting from overspecialization) can appear as novel if the user is searching an item for the first time. However, as previously discussed, RAs activates a journey that mimic the WOM until the final purchase (Ansari et al., 2000). As a result, when RAs find an item that match users' preferences, they start to recommend it until the final choice occurs (Ansari et al., 2000). According to Sawyer (1981), if a stimulus is repeated, individuals will become accustomed to the stimulus but becoming bored due to the repetition and the increasing familiarity. Conversely, novelty is a constant way to enlarge the RS with new products, far from users' preferences. It benefits both users, which are not imprisoned in their *user profile* anymore, and e-tailers which can acquire new ratings for unpopular products.

Therefore, assuming the existing contributions and knowledge gap on the effects RAs novelty on users choice outcomes, I hypothesize that higher degrees of novelty are preferred by users and results in greater outcomes. Specifically,

H_5: Novel RSs results in higher sense of novelty and, in turn, in higher choice outcomes

Overview of the studies

In a sequence of four studies I aim to understand the effects of overspecialization on users' choice outcomes, its antecedents and a potential interventions that may lessen the risk of "tight" recommendations. Study 1 investigates how increasing levels of RAs specialization may reduce the users' outcomes. Study 2 sheds light on the antecedents of the acceptance/rejection of overspecialization by assessing the perceived reciprocity and intimacy conveyed by generalised and overspecialised RAs. Study 3 assesses the overspecialization as a factor that may reduce the formation of new preferences and negatively affects the breadth of users' knowledge and, subsequently, the users outcomes. Finally, study 4 evaluates the effectiveness of algorithmic novelty as a way to counteract RAs overspecialization and the decrease of choice outcomes.

Study 1

In this first study, I started from examining the effects of RAs overspecialization on consumer choice outcomes. While prior literature has extensively discussed how to model the accuracy from an algorithmic standpoint and the benefits of accurate recommendations, I posit that RAs overspecialization reduce the chance to form new preferences and results in lower choice outcomes. To test the hypotheses, I varied the RAs degree of specialization in 3 different ways, generalised, specialized and overspecialized and verified the associated outcomes to the manipulation .

Method

Participants. A total of 358 participants (176 women; M_{age}= 26 years, SD= 3.86) completed the study and were monetary rewarded after completion. The participants were recruited on Prolific.co. They were filtered according to their past purchase experiences on online platforms such that non-users or low-user were not included in the study (See Appendix 1).

Procedure. I implemented a 3 x 1 design to examine the effects of RAs overspecialization on choice outcomes. In this study, I divided the concept of RAs knowledge from the ability to provide novel products. In my idea, accurate RSs are the effect of specialized and overspecialized RAs. This implies that the RSs is an output of a process where RAs continuously form their knowledge (i.e., the input).

In the present study, I varied only the level of knowledge of RAs as the only engine that consequently produces diverse or accurate recommendations. In the initial sections of the survey, respondents received the information about the focus on RAs and a short description about the agent.

Subsequently, respondents were exposed to three different conditions, with a generalised RA (i.e., absence of knowledge of users preferences), specialised RA (i.e., quite informed about users preferences) and an overspecialized RA (i.e., many information about users preferences). To manipulate the degree of knowledge of the RA, I requested to respondents to do an elicitation task which is activated in the reality by RAs to infer user preferences. Indeed, in the condition dominated by an overspecialized RA, users were asked to repeat for three times an evaluation of eight smart bands. In the first assessment, a statement anticipating the absence of information about the user preferences and the generation of the recommendation according to available data were submitted to participants before assessing the products. After reading the statement, they assessed the first four products according to their preferences. The initial evaluation led them to the second assessment. In the meanwhile, they were exposed to a loading page and forced to wait for new recommendations for 10 seconds. At the completion of the loading, they started the second assessment and have been told about the increased knowledge of the RA, thanks to their antecedent elicitation task, and to provide new information to increase again the understanding of the RA about their user preferences. Finally, after the second elicitation task, they have been exposed to a new loading page for 10 seconds and then exposed to the final set of recommendations, which took into account the product they liked the most. Whilst users exposed to the generalised RA, were stopped to the first task while those exposed to the specialised RA were stopped to the second task. Before the recommendations, users have always been exposed to the loading page to made the elaboration of RAs realistic. The recommended options in the conditions with the specialised RA and overspecialized RA, were computed according to their preferences; the firsts have been exposed to two products that they have positively assessed in the elicitation tasks plus two other random products while the latter have been exposed to the two most-rated products of the first task and the two most-rated in the second task. If three products or four products received the same score, they were randomly recommended to the user.

Manipulation check. As a manipulation check, I assessed the perception of the level of RA's specialization by asking to 50 respondents to rate the perceived expertise of the RA (1= Very Low Expertise and 7= Very High Expertise).

Measures. After viewing the final RS, respondents answered to the choice outcomes scales. The perceived usefulness scale (α=.901) (Hsieh et al., 2021), enjoyment (i.e., single item), willingness to accept the recommendation (α=.864), satisfaction (i.e., single item) (Kim et al., 2021; Komiak et al., 2006), perceived benefit of the recommendation (α=.849) (Su et al., 2008) scales were adapted from the extant literature (Figure 2). The items were measured on a seven-point Likert scales (1 = "strongly disagree," and 7 = "strongly agree"). I also collected data about the gender, education, income, age and the frequency of online shopping.

Results

Manipulation check. Participants, when exposed to more elicitation tasks, consider RAs as more expert (M = 4.50, SD = 1.85), while the perceived expertise decreases in specialised (M = 4.48, SD = 1.85) and generalised conditions (M = 4.36, SD = 1.85). Hence, respondents correctly associated the number of elicitation tasks to the increase of RAs specialization.

Choice outcomes

Usefulness. The analysis of variance highlighted a significant main effect of the manipulation on the perceived usefulness of the recommendation ($F(1, 357) = 2.621$; $p < .05$). Respondents perceive the generalised algorithms as more useful ($M_{GeneralisedRA}$=5.01; SD=1.22) than specialised ($M_{SpecialisedRA}$=4.77; SD=1.33) and overspecialised RAs ($M_{OverspecializedRA}$=4.62; SD=1.42).

Willingness to adopt the Recommender Agents. A one-way ANOVA revealed a significant main effect of the degree of specialization of the algorithm on the willingness to adopt the RA ($F(1, 357) = .837$; $p < .05$). Overspecialised RAs rely on lower degrees of willingness to adopt the RA ($M_{OverspecializedRA}$=4.12; SD=1.45) than specialised ($M_{SpecialisedRA}$=4.17; SD=1.32) and generalised RAs ($M_{GeneralisedRA}$=4.34; SD=1.32).

Perceived Benefit. The perceived benefit of the recommendation is significantly affected by the RAs degree of specialization ($F(1, 357) = 4.620$; $p < .05$). Generalised RAs are significantly perceived as more beneficial ($M_{GeneralisedRA}$=5.13; SD=1.18) than the others conditions ($M_{SpecialisedRA}$=4.71; SD=1.43 vs. $M_{OverspecializedRA}$=4.65; SD=1.34).

Enjoyment. The analysis of variance reported a significant main effect of the RAs degree of specialization on User's Enjoyment ($F(1, 357) = .781$; $p < .05$). Indeed, generalised RAs ($M_{GeneralisedRA}$=4.99; SD=1.43) are enjoyed more than specialised and overspecialised RAs ($M_{SpecialisedRA}$=4.76; SD=1.65 vs. $M_{OverspecializedRA}$=4.77; SD=1.65).

Satisfaction. A significant main effect of the RAs degree of specialization on users' satisfaction toward the recommendation has been highlighted by the one-way ANOVA ($F(1, 357) = .781$; $p < .05$). Respondents are more satisfied with recommendation generated by generalised RAs ($M_{GeneralisedRA}$=4.90; SD=1.23) than specialised and overspecialised RAs ($M_{SpecialisedRA}$=4.70; SD=1.58 vs. $M_{OverspecializedRA}$=4.65; SD=1.48) (see Figure 3).

Studies	Items	References
Studies 1,2,3,4	*Usefulness*	Hsieh, S. H., & Lee, C. T. (2021)
	The RA provides good quality information	
	The RA increases my effectiveness for informed choices online	
	The RA is useful for assessing information choices online	
	The RA improves my performance in assessing information choices	
Studies 1,2,3,4	*Willingness to adopt the Ras*	Komiak, S. Y., & Benbasat, I. (2006)
	I am willing to delegate to this RA for my decision about which product to buy.	
	I am willing to let this RA decide which product to buy on my behalf.	
	I am willing to use this RA as an aid to help with my decision about which product to buy.	
	I am willing to let this RA assist me in deciding which product to buy.	
	I am willing to use this RA as a tool that suggests to me a number of products from which I can choose	
Studies 1,2,3,4	*Perceived Benefit*	Su, H. J., Comer, L. B., & Lee, S. (2008).
	The quality of recommendations I obtained improved my decision making	
	A lot of alternatives were examined	
	It was worthwhile to look for recommendations before making the decision	
Studies 1,2,3,4	*Enjoyment*	Kim, A., Affonso, F. M., Laran, J., & Durante, K. M. (2021)
	How much did you enjoy the painting? (1 = “not at all,” and 7 = “very much”)	
Studies 1,2,3,4	*Satisfaction*	Kim, A., Affonso, F. M., Laran, J., & Durante, K. M. (2021)
	How satisfied are you with the prod- ucts you received?” (1 = “not at all satisfied,” and 7 = “very satisfied”)	
Study 2	*Reciprocity*	Lee, S. Y., & Choi, J. (2017)
	The RA gave good responses to your questions.	
	I felt that the RA was like my companion or friend.	
	The RA was helpful when you asked for information.	
	I think the RA and I were able to help each other.	
	I think the RA and I exchanged opinions as though we were equal in our social status.	
	I felt solidarity with the RA after our conversation.	
	I think the RA will support me emotionally.	
Study 2	*Intimacy*	Lee, S. Y., & Choi, J. (2017)
	I feel close to the RA.	
	I feel that the RA is my close friend.	
	I feel emotionally close to the RA.	
	I think the RA will affect my selection of media contents.	
	The RA uses supportive statements to build favor with me.	
	I developed a sense of familiarity with the RA.	
Study 3	*Breadth and Depth of Knoweldge*	Clarkson, J. J., Janiszewski, C., & Cinelli, M. D. (2013)
	How much would seeing this recommendations help you to understand the differences between various type of movies?	
	How much would seeing this recommendations help you to understand the similarities between movies within your preferred genres of movies?	
	How much would seeing this recommendations help you to categorize new movies within the broad types of movies?	
	How much would seeing this recommendations help you to categorize new movies within your preferred genres of movies?	
	How much would seeing this recommendations increase your familiarity with the various type of movies?”	
	How much would seeing this recommendations increase your familiarity with the assortment of movies available within your preferred genre of movies?	
Study 4	*Feelings of novelty*	Söderlund, M., & Mattsson, J. (2019)
	“The outcome was unexpected,”	
	“I became surprised”	
	“I could not have known before exactly what would happen”	

Table 1. Measures and scales

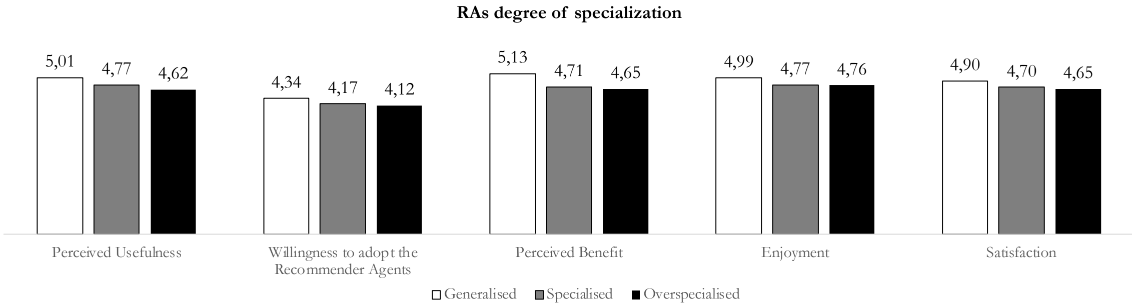

Figure 2. Mean differences associated to RAs degree of specialization

Discussion

In accordance with the prediction, the Study 1 proved that over-specialized RAs with high levels of knowledge about users lead to lower choice outcomes, meaning that users prefer even less accurate RAs that are not a mere reflection of their preferences. Importantly, accurate RAs are seen as a way to bound users' preferences to existing ones and limit the chances to form new preferences.

Study 2

In study 2, I assessed the antecedents of the rejection of RAs overspecialization. I posited that reciprocity and intimacy are negatively affected by RAs overspecialization due to the increasing knowledge which is not reciprocate with users. This study fulfil an existing gap in the literature which deeply investigate the reciprocity and intimacy without focusing on RAs overspecialization. I manipulated two different level of RAs expertise and assessed the effects on the perceived reciprocity, intimacy (as mediators) and choice outcomes. I expect that higher levels of RAs expertise are associated to lower levels of reciprocity and intimacy due to the absence of shared knowledge and chances for the user to form new preferences.

Method

Participants. A total of 304 online shoppers (151 women; M_{age}= 31 years, SD= 3,47) were recruited on Prolific.co and rewarded after completion. Those who have few or inexistent experiences on online platforms were not withdrawn from the study (See Appendix 1).

Procedure. Study 2 assess the impact of RAs overspecialization on two mediators, reciprocity and intimacy, and choice outcomes. In this study, I replied the procedure of Study 1 while modifying the product category (i.e., face cream) and the levels of RAs expertise (high vs. low). Respondents were randomly assigned to the high and low conditions. Those exposed to the expert RA did a preference elicitation task twice, while those in the generalised condition were directly exposed to the final RS. Considering the nature of the product category, the elicitation tasks and the RSs, were altered according to the gender of the respondents. A summary of the functionalities of RAs has been offered to respondents without deepening the pros, cons or computational details. After every elicitation tasks and before the final RS, user have seen a loading page which fictitiously provide the idea about the underlying computation made by the RA. As in study 1, all the final recommendations set have been computed according to the preferences elicited by users.

Manipulation check. The manipulation check on 50 participants, allowed to measure the perceived expertise of generalised, and overspecialised RAs by asking to assess after each elicitation tasks the expertise of the agent on a seven-point scales (1= Very Low Expertise and 7= Very High Expertise).

Measures. At the completion of the recommendation process, respondents assessed the perceived reciprocity through "the RA gave good responses to your questions", "I felt that the RA was like my companion or friend", "The RA was helpful when you asked for information", "I think the RA and I were able to help each other", "I think the RA and I exchanged opinions as though I were equal in our social status", "I felt solidarity with the RA after our conversation", "I think the RA will support me emotionally" (Lee et al., 2017) and the intimacy through "I feel close to the RA", "I feel that the RA is my close friend", "I feel emotionally close to the RA", "I think the RA will affect my selection of contents", "the RA uses supportive statements to build favor with me", "I developed a sense of familiarity with the RA" (Lee et al., 2017). The items of reciprocity and intimacy scale were combined to form the reciprocity (α=.927) and intimacy (α=.920) construct. As per Study 1, they answered to the perceived usefulness scale (α=.870) (Hsieh et al., 2021), enjoyment (i.e., single item), willingness to adopt the RA (α=.828)(Komiak et al., 2006), satisfaction (i.e., single item) (Kim et al., 2021; Komiak et al., 2006), perceived benefit of the recommendation (α=.822) (Su et al., 2008) (Figure 2). All the items all measured on a seven-point Likert scales. I also collected data about the gender, the education, the age and the frequency of online shopping.

Results

Manipulation check. The level of RAs degree of specialization is properly perceived as higher as the number of elicitation task they are exposed to. This study implies only two level of the categorical variable indicating the high and low expertise of RAs. After two elicitation tasks, the perception of RAs degree of specialization was higher than the initial situation ($M_{initialmeasurement}$ = 4.27, SD = 1.41 vs. $M_{finalmeasurement}$ = 4.74, SD = 1.53). Thus, participants discriminate the degrees of RAs specialization according to the level of information acquired by RAs and the number of elicitation tasks.

Choice outcomes

Usefulness. An independent t-test highlighted a significant difference between (t(1, 302) = 1.191; $p < .01$) between generalised and overspecialised RAs in terms of usefulness. The generalised algorithm are perceived as more useful ($M_{GeneralisedRA}$=4.93; SD=1.09) than overspecialised RAs ($M_{OverspecialisedRA}$=4.77; SD=1.23).

Willingness to adopt the Recommender Agents. A significant difference between the two conditions (overspecialised vs. generalised) has been reported through an independent t-test (t(1, 302) = .165; $p < .05$). Overspecialised RAs are associated to lower degrees of willingness to adopt the RA ($M_{OverspecialisedRA}$ =4.38; SD=1.28) than generalised RAs ($M_{GeneralisedRA}$=4.41; SD=1.14).

Perceived Benefit. The perceived benefit of the recommendation significantly varies according to the RA expertise (t(1, 302) = 1.246; $p < .01$). The t-test reported that generalised RAs are perceived as more beneficial ($M_{GeneralisedRA}$=5.02; SD=1.18) than the overspecialised RAs ($M_{OverspecialisedRA}$=4.85; SD=1.23).

Enjoyment. Also, the User's Enjoyment significantly differs according to the RAs level of specialization (t(1, 302) = .346; $p < .01$). Generalised RAs ($M_{GeneralisedRA}$ =4.83; SD=1.37) rely on higher degrees of enjoyment than overspecialised RAs ($M_{OverspecialisedRA}$ =4.77; SD=1.58).

Satisfaction. A significant difference across the levels of RAs specialization has been revealed by the independent t-test (t(1, 302) = 1.104; $p < .01$). Respondents are more satisfied with recommendation generated by generalised RAs ($M_{GeneralisedRA}$=4.87; SD=1.24) than overspecialised RAs ($M_{OverspecialisedRA}$=4.70; SD=1.38).

Mediation by Reciprocity and Intimacy. I ran a bootstrapping sequential mediation analysis (PROCESS Model 6; Hayes 2018) using the level of specialization of the RAs (high vs. low) as the independent variable, the perceived reciprocity and intimacy as sequential mediators and the choice outcomes as dependent variables (see Table 1). For the usefulness measure the index of sequential mediation was significant (β: -0.059, 95% CI: [-0.080, -0.037]). The degree of specialization negatively affects the reciprocity (β:- .183, SE: .056) which in turn positively influence the intimacy (β: .874, SE: .029) that impacts the DV (β: .368, SE: .068). Since the direct effect is not significant, the results suggest a full mediation. As for the second measure, the effect of RAs specialization on willingness to adopt the recommender agents is mediated by both reciprocity and intimacy (β: -0.050, 95% CI: [-0.069, -0.0031]). The other effects remain unchanged while the effect of intimacy on RAs specialization has changed (β: .0314, SE: .065). Similarly, the effect on perceived benefit and satisfaction are mediated by reciprocity and intimacy ($\beta_{PerceivedBenefit}$: -0.038, 95% CI: [-0.055, -0.020]; $\beta_{Satisfaction}$: -0.036, 95% CI: [-0.053, - 0.019]. Also, the effects of intimacy on the DVs are significant ($\beta_{PerceivedBenefit}$: .0239, SE: .078 vs. $\beta_{Satisfaction}$: .0230, SE: .079) while the other effects remain stable. Finally, a full serial mediation has been reported (β: -0.042, 95% CI: [-0.061, -0.024]).

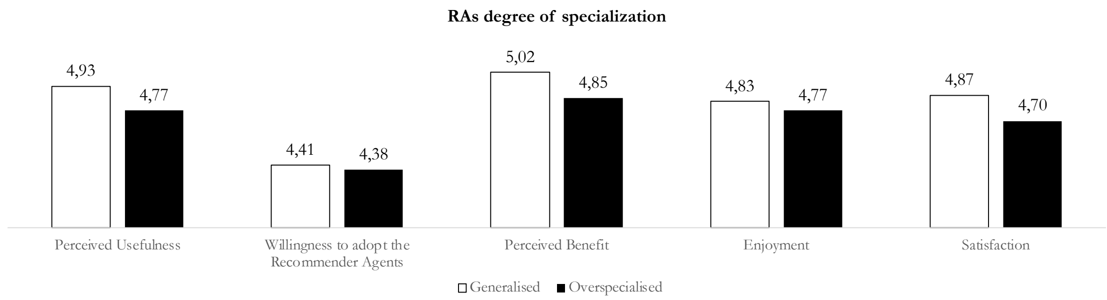

Figure 3. Mean differences associated to RAs degree of specialization

Path	Path Coefficient (β)	SE	*p*
Usefulness			
RAs Specialization Degree → Choice Outcomes	-0.115	0.097	
RAs Specialization Degree → Reciprocity	-0.183	0.056	***
Reciprocity → Intimacy	0.874	0.029	***
Intimacy → Choice Outcomes	0.368	0.068	***
RAs Specialization Degree → Reciprocity → Intimacy → Choice Outcomes	-0.059	0.021	CI[-0.080, -0.037]
Willingness to adopt the RA			
RAs Specialization Degree → Choice Outcomes	-0.031	0.094	
RAs Specialization Degree → Reciprocity	-0.183	0.057	***
Reciprocity → Intimacy	0.874	0.029	***
Intimacy → Choice Outcomes	0.314	0.065	***

RAs Specialization Degree → Reciprocity → Intimacy → Choice Outcomes	-0.050	0.018	CI[-0.069, -0.031]
Perceived Benefit			
RAs Specialization Degree → Choice Outcomes	-0.127	0.109	
RAs Specialization Degree → Reciprocity	-0.183	0.057	***
Reciprocity → Intimacy	0.874	0.029	***
Intimacy → Choice Outcomes	0.239	0.078	***
RAs Specialization Degree → Reciprocity → Intimacy → Choice Outcomes	-0.038	0.017	CI[-0.055, -0.020]
Enjoyment			
RAs Specialization Degree → Choice Outcomes	-0.010	0.087	
RAs Specialization Degree → Reciprocity	-0.183	0.056	***
Reciprocity → Intimacy	0.874	0.029	***
Intimacy → Choice Outcomes	0.268	0.081	***
RAs Specialization Degree → Reciprocity → Intimacy → Choice Outcomes	-0.042	0.018	CI[-0.061, -0.0241]
Satisfaction			
RAs Specialization Degree → Choice Outcomes	-0.124	0.113	
RAs Specialization Degree → Reciprocity	-0.183	0.057	***
Reciprocity → Intimacy	0.874	0.029	***
Intimacy → Choice Outcomes	0.230	0.079	***
RAs Specialization Degree → Reciprocity → Intimacy → Choice Outcomes	-0.036	0.017	CI[-0.0538, -0.0196]

Table 2. Direct and Indirect effect of Study 2

Discussion

Study 2 support the H_2 and contributes to the understanding of algorithm overspecialization. First, as proved in study 1, I confirm that choice outcomes increase when the degree of knowledge of the RA is lower. Second, when users only receive recommendations by an algorithm that is learning about them, they feel a lack of reciprocity and intimacy. It might depend on several factors (e.g., privacy concerns) but without a more developed exchange of information between RAs and users, the latter will tend to prefer generalised algorithm as a way to form new preferences and as partner able to reciprocate.

Study 3

In study 3 I continued with the investigation of the antecedent of the rejection of overspecialization. In my idea the everlasting attempt to provide user with accurate RAs, generated a countereffect that results in a reduction of the chances to form new preferences. It happens for both expert and non-expert users: they can't increase their expertise through the exposure to products distant from their preferences and are confined to their extant knowledge without having the chance to expand their preferences and their expertise. In this study, I manipulated the (1) RAs knowledge exposing respondents to agents with breadth and depth knowledge and measured the effect of this manipulation on the user's expertise and choice outcomes.

Method

Participants. 362 participants (178 women; M_{age}= 27 years, SD= 4.51) have been recruited through Prolific.co and completed the study after being rewarded. They were filtered according to the frequency of online shopping. Participants with a low or null frequency of online shopping were not accepted for the subsequent stages (See Appendix 1).

Procedure. I implemented a 2 x 1 design to examine the effects of RAs type of knowledge on the users' breadth and depth knowledge and on choice outcomes. In this study, I manipulated the RAs type of knowledge by exposing respondents to two different conditions. I initially asked them their preferred movie genre: comedy, thriller, sci-fi and fantasy. I leveraged on movies recommendations as services which are frequently adopted by users to discover new movies and for the width of movie genres that ensure the likelihood to find well-known and never-seen-before products. After the selection of their preferred genre, they were randomly assigned to RAs with breadth or depth knowledge. Depth RSs refer to the four preferred items that have been previously selected by respondents in a larger set of 8 movies. Breadth recommendations sets refer to items of the same movie genre but never rated by the respondent. Before the exposure to breadth and depth RAs, respondents were asked to select their 4 preferred movies in a selection 8 movies of the genres. After the selection, they were assigned to a loading page for 10 seconds and then to the recommendations. After receiving the final set of recommendations, they were exposed to the measures.

Manipulation check. As a manipulation check, I assessed the type of knowledge of RAs. After exposing them to the initial tasks, I asked them to rate their perception of the breadth or depth of the RS on a seven-point scale (1= Breadth and 7= Depth). The definition of the two categories have been previously described before the assessment.

Measures. Once they have received the recommendations, I measured all the variables i.e., perceived usefulness scale (α=.878) (Hsieh et al., 2021), willingness to accept the recommendation (α=.853)(Komiak et al., 2006), perceived benefit of the recommendation (α=.881) (Su et al., 2008), enjoyment (single item) and satisfaction (single item) (Kim et al., 2021). Moreover, I assessed their enhancement of breadth knowledge style by asking them "How much would seeing this recommendations help you to understand the differences between various type of movies?", "How much would seeing this recommendations help you to categorize new movies within the broad types of movies?", "How much would seeing this recommendations increase your familiarity with the various type of movies?" and of the depth knowledge through "How much would seeing this recommendations help you to understand the similarities between movies within your preferred genres of movies?", "How much would seeing this recommendations help you to categorize new movies within your preferred genres of movies?", "How much would seeing this recommendations increase your familiarity with the assortment of movies available within your preferred genre of movies?" (Clarkson et al., 2013). The items were the combined to form a sole construct (α=.897) (Figure 2). All the items were measured on a seven-point Likert scales (1 = "strongly disagree," and 7 = "strongly agree"). I also collected data about the gender, the education, the age and the frequency of online shopping.

Results

Manipulation check. An independent t-test highlighted a significant mean difference between the two condition ($t(1, 360) = -2.154$; $p < .05$). The overspecialised RS is properly perceived as more able to provide accurate and tailored information ($M_{overspecialised} = 4.98$, $SD = 1.22$) than generalised RAs ($M_{generalised} = 4.66$, $SD = 1.57$). Hence, participants attach different levels of knowledge to overspecialised and generalised RAs.

Mediation by Breadth and Depth of Knowledge. A parallel mediation analysis (PROCESS Model 4; Hayes 2020) has been outlines using the RAs degree of specialization, generalised (coded as 1) vs. specialised (coded as 0), as the independent variable, the enhancement of breadth and depth of knowledge as mediators and the choice outcomes as dependent variables (see Table 2). The relationship between the IV and usefulness was significantly mediated by both breadth and depth ($\beta_{breadth}$: 0.156, 95% CI: [0.014,0.310]; β_{depth}: 0.056, 95% CI: [0.003,0.136]). The RAs knowledge positively affects the enhancement of the breadth and depth of knowledge ($\beta_{breadth}$: .320, SE: .149; β_{deptth}: .3445, SE: .136) which in turn positively influence the usefulness ($\beta_{breadth}$: .4897, SE: .056; $\beta_{depttth}$: .163, SE: .061). The direct effects are not significant indicating a full mediation in both cases. The magnitude of the effect is higher for the breadth of knowledge. A result also confirmed by a t-test, such that respondents consider generalised RAs, able to diverge from their preferences with recommendations involving generic products, more useful than overspecialised RAs ($M_{breadth}$: 5.04, SD: 1.03; M_{depth}: 4.84, SD: 1.46).

Whilst, the effects on willingness to adopt the recommender agents, are mediated by the breadth and depth of knowledge ($\beta_{breadth}$: 0.142, 95% CI: [0.015,0.290]; β_{depth}: 0.079, 95% CI: [0.014,0.167]). The influence of the DV on the mediators remains unchanged ($\beta_{breadth}$: .320, SE: .148; $\beta_{depttth}$: .344, SE: .136) while the effects of the mediators on the willingness to adopt the RA have changed ($\beta_{breadth}$: .445, SE: .060; $\beta_{depttth}$: .231, SE: .065). When mediated by the breadth and depth of knowledge, the direct effect of the RAs are not significant, indicating a full mediation. Similar to the previous DV, generalised RAs are associated to the breadth of knowledge which, in turn, is associated to a higher willingness to adopt the RA ($M_{breadth}$: 4.46, SD: 1.17). Conversely, the overspecialised RAs which mainly affect the depth of knowledge, are associated to lower level of willingness to adopt the RA (M_{depth}: 4.12, SD: 1.37).

The effects on perceived benefit are also mediated by the two mediators ($\beta_{breadth}$: 0.135, 95% CI: [0.012,0.2681]; β_{depth}: 0.113, 95% CI: [0.023,0.224]). While the effects of IV on the mediators are the same, the influence of the two mediators on the DV is not ($\beta_{breadth}$: .423, SE: .055; $\beta_{depttth}$: .328, SE: .060). The relationship, even in this case, is fully mediated since the effect of the IV on the DV is not significant. Generalised RAs mainly affect the breadth of knowledge and are associated to higher levels of perceived benefit ($M_{breadth}$: 5.04, SD: 1.11 vs. M_{depth}: 4.39, SD: 1.44).

As for the satisfaction, I observed a full mediation in both cases ($\beta_{breadth}$: 0.104, 95% CI: [0.012,0.218]; β_{depth}: 0.0964, 95% CI: [0.020,0.194]) since the effect of the DV on the IV is not significant. The effects of the two mediators on the DV are positive but with a different magnitude ($\beta_{breadth}$: .326, SE: .056; $\beta_{depttth}$: .279, SE: .062). Overspecialised RAs are associated to higher effects on the depth of knowledge to which respondents attach less satisfaction (M_{depth}: 4.55, SD: 1.30) than generalised RAs which positively affect the breadth of knowledge and result in higher levels of satisfaction ($M_{breadth}$: 5.02, SD: 1.09).

Finally, the effect of the DV on enjoyment is fully mediated in both analysis ($\beta_{breadth}$: 0.169, 95% CI: [0.015,0.349]; β_{depth}: 0.077, 95% CI: [0.005,0.180]). Both depth and breadth of knowledge positively affect the enjoyment ($\beta_{breadth}$: .529, SE: .068; β_{deptth}: .225, SE: .074) while the effect of the degree of specialization of the RA is not significant. Generalised RAs are associated to higher levels of breadth of knowledge and enjoyment ($M_{breadth}$: 5.28, SD: 1.25 vs. M_{depth}: 4.87, SD: 1.61).

Path	**Path Coefficient (β)**	**SE**	***p***
Usefulness			
RAs Specialization Degree → Choice Outcomes	0.169	0.091	
RAs Specialization Degree → Breadth	0.320	0.149	***
RAs Specialization Degree → Depth	0.344	0.136	***
Breadth → Choiche Outcomes	0.489	0.056	***
Depth→ Choiche Outcomes	0.163	0.061	***
RAs Specialization Degree → Breadth → Choice Outcomes	0.156	0.074	CI[0.0140, 0.3103]
RAs Specialization Degree → Depth → Choice Outcomes	0.056	0.034	CI[0.0036, 0.1368]
Willingness to adopt the RA			
RAs Specialization Degree → Choice Outcomes	0.119	0.097	
RAs Specialization Degree → Breadth	0.320	0.149	***
RAs Specialization Degree → Depth	0.344	0.136	***
Breadth → Choiche Outcomes	0.445	0.060	***
Depth→ Choiche Outcomes	0.231	0.066	***
RAs Specialization Degree → Breadth → Choice Outcomes	0.142	0.070	CI[0.0151, 0.2903]
RAs Specialization Degree → Depth → Choice Outcomes	0.079	0.039	CI[0.0143, 0.1676]
Perceived Benefit			
RAs Specialization Degree → Choice Outcomes	0.398	0.090	
RAs Specialization Degree → Breadth	0.320	0.149	***
RAs Specialization Degree → Depth	0.344	0.136	***
Breadth → Choiche Outcomes	0.423	0.056	***
Depth→ Choiche Outcomes	0.328	0.061	***
RAs Specialization Degree → Breadth → Choice Outcomes	0.135	0.066	CI[0.0120, 0.2681]
RAs Specialization Degree → Depth → Choice Outcomes	0.113	0.052	CI[0.0239, 0.2247]
Enjoyment			
RAs Specialization Degree → Choice Outcomes	0.168	0.111	
RAs Specialization Degree → Breadth	0.320	0.149	***
RAs Specialization Degree → Depth	0.344	0.136	***
Breadth → Choiche Outcomes	0.529	0.069	***
Depth→ Choiche Outcomes	0.225	0.075	***
RAs Specialization Degree → Breadth → Choice Outcomes	0.169	0.084	CI[0.0153, 0.3495]
RAs Specialization Degree → Depth → Choice Outcomes	0.077	0.046	CI[0.0059, 0.1809]
Satisfaction			

RAs Specialization Degree → Choice Outcomes	0.266	0.092	
RAs Specialization Degree → Breadth	0.320	0.149	***
RAs Specialization Degree → Depth	0.344	0.136	***
Breadth → Choiche Outcomes	0.326	0.057	***
Depth→ Choiche Outcomes	0.279	0.062	***
RAs Specialization Degree → Breadth → Choice Outcomes	0.104	0.053	CI[0.0122, 0.2185]
RAs Specialization Degree → Depth → Choice Outcomes	0.096	0.044	CI[0.0200, 0.1943]

Table 3. Direct and Indirect effects of RAs degree of specialization on choice outcomes and mediators

Discussion

Study 3 confirms our H_3 and H_4. RAs exert an effect on choice outcomes that is mediated by the depth and depth of knowledge. It indicates that before forming outcomes users develop, with a different magnitude, the breadth and depth of knowledge. Moreover, RAs with lower levels of specialization benefit more the breadth of knowledge rather than the depth, meaning that users mainly adopt RAs to develop by observing new items.

Study 4

In study 4, I examined the algorithmic novelty as potential solution to counteract the overspecialization. Specifically, the hypothesis is that users prefer RSs characterized by the constant presence of products never seen before and even distant from their preferences rather than accurate recommendations.

Method

Participants. A sample of 301 participants (151 women; M_{age}= 26 years, SD= 2.98) completed the survey and were rewarded after completion. They were all online users with past experience in shopping online on common online marketplaces (See Appendix 1).

Procedure. In this study, I manipulated the degree of novelty of the RS generated by RAs. Two different conditions were randomly assessed by respondents. In the condition of accurate recommendations, respondents assessed a RS generated by an overspecialized RA. Whilst, in novel-based algorithm, I proposed a set of products as never seen before. I framed the users by describing the nature of the two RAs: one accurate and precise which provide users with tailored information and another one who provide users with products even far from their preferences. After reading the description, they have been exposed to a loading page and waited for the completion for 10 seconds. Then, they were redirected to the RS with 4 products (i.e., smart band).

Manipulation check. As a manipulation check, I preliminarily assessed the perceived novelty of the RS. Respondents were randomly assigned to a novel-based algorithm and a specialized one. Then, I asked them to rate the perceived degree of novelty of the RS on a seven-point scale (1= Very Low and 7= Very High).

Measures. Perceived usefulness scale (α=.858) (Hsieh et al., 2021), enjoyment (i.e., single item), willingness to accept the recommendation (α=.846), satisfaction (i.e., single item) (Kim et al., 2021; Komiak et al., 2006), perceived benefit of the recommendation (α=.834) (Su et al., 2008) were assessed after the exposure to the recommendation. Moreover, I assessed their sense of novelty style by asking them "I feel that the products I received from the company were new, "I feel lucky to have come across these products", "I feel that these products were an unexpected discovery" (Alexandrov et al., 2020). The items were then combined to form a sole construct (α=.788). All the items were measured on a seven-point Likert scales (1 = "strongly disagree," and 7 = "strongly agree") and I also collected socio-demographic data (i.e., gender, the education, the age and the frequency of online shopping) (Figure 2).

Results

Manipulation check. An independent t-test highlighted a significant mean difference between the two dataset ($t(1, 60) = 1.327$; $p < .001$). The novel-based RS is properly perceived as more novel ($M_{novel} = 5.03$, SD = 1.15) than accurate RSs ($M_{accurate} = 4.61$, SD = 1.30).Thus, participants properly discriminated the differences between novel and accurate RAs and perceived the latter as less novel than the others.

Choice outcomes

Usefulness. An independent t-test highlighted a significant difference between ($t(1, 299) = 1.896$; $p < .05$) between novel-based RAs and accurate RAs in terms of usefulness. The novel-based algorithm are perceived as more useful ($M_{NovelRA}$=5.06; SD=1.06) than accurate RAs ($M_{AccurateRA}$=4.83; SD=1.03).

Willingness to adopt the Recommender Agents. A significant difference between the two conditions (novelty vs. accuracy) has been reported through an independent t-test ($t(1, 299) = 2.063$; $p < .05$). Accurate RAs are associated to lower degrees of willingness to adopt the RA ($M_{AccurateRA}$=4.11; SD=1.24) than novelty-based RAs ($M_{NovelRA}$=4.42; SD=1.32).

Perceived Benefit. The perceived benefit of the recommendation significantly varies according to the type of RA ($t(1, 299) = 1.238$; $p < .01$). The t-test reported that novelty-based RAs are perceived as more beneficial ($M_{NovelRA}$=5.05; SD=1.24) than the accurate RAs ($M_{AccurateRA}$=4.87; SD=1.18).

Enjoyment. Also, the User's Enjoyment significantly differs according to the RAs ability to provide novel recommendations ($t(1, 299) = .124$; $p < .05$). Novelty-based RAs ($M_{NovelRA}$=4.50; SD=1.22) rely on higher degrees of enjoyment than accurate RAs ($M_{AccurateRA}$=4.39; SD=1.06).

Satisfaction. A significant difference across the levels of RAs novelty has been revealed by the independent t-test ($t(1, 299) = 1.312$; $p < .05$). Respondents are more satisfied with novel recommendation ($M_{NovelRA}$=4.93; SD=1.09) than accurate ones ($M_{AccurateRA}$=4.76; SD=1.15).

Mediation by Sense of Novelty. I ran a bootstrapping mediation analysis (PROCESS Model 4; Hayes 2020) using the level of novelty of the RS (novel vs. accurate) as the independent variable, the sense of novelty as mediator and the choice outcomes as dependent variables (see Table 4). For the usefulness measure the index of mediation was significant (β: 0.0523, 95% CI: [0.0042,0.1830]). The degree of novelty positively affects the sense of novelty (β: .1083, SE: .1325) which in turn positively influence the usefulness (β: .4833, SE: .0453). The direct effect is not significant indicating a full mediation.

As for the effect on willingness to adopt the recommender agents, the effect of RAs novelty is mediated by the sense of novelty (β: 0.0683, 95% CI: [0.0109,0.2364]). While the effect of the DV on the mediator remains unchanged, the effect of the sense of novelty on the willingness to adopt the RA has changed (β: .6308, SE: .0536). The effects on perceived benefit and satisfaction are mediated by the sense of novelty ($\beta_{PerceivedBenefit}$: 0.0561, 95% CI: [0.0007,0.1974]; $\beta_{Satisfaction}$: 0.0505, 95% CI: [0.0011,0.1821]. Also, the effects of sense of novelty on the DVs are significant ($\beta_{PerceivedBenefit}$: .5184, SE: .0535 vs. $\beta_{Satisfaction}$: .4660, SE: .0506) while the other effects remain stable. The effects on enjoyment were not significant.

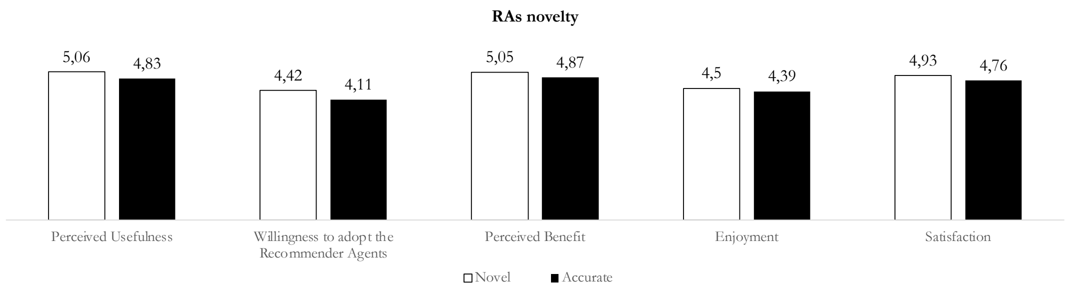

Figure 4. Mean differences associated to RSs degree of novelty

Path	**Path Coefficient (β)**	**SE**	***p***
Usefulness			
RAs Specialization Degree → Choice Outcomes	0.178	0.104	
RAs Specialization Degree → Sense of Novelty	0.108	0.133	*
Sense of Novelty → Choice Outcomes	0.483	0.045	***
RAs Specialization Degree → Sense of Novelty → Choice Outcomes	0.052	0.066	CI[0.0042, 0.1839]
Willingness to adopt the RA			
RAs Specialization Degree → Choice Outcomes	0.237	0.123	
RAs Specialization Degree → Sense of Novelty	0.108	0.133	*
Sense of Novelty → Choice Outcomes	0.630	0.054	***
RAs Specialization Degree → Sense of Novelty → Choice Outcomes	0.068	0.059	CI[0.0093, 0.1273]
Perceived Benefit			
RAs Specialization Degree → Choice Outcomes	0.117	0.123	
RAs Specialization Degree → Sense of Novelty	0.108	0.133	*
Sense of Novelty → Choice Outcomes	0.518	0.535	***
RAs Specialization Degree → Sense of Novelty → Choice Outcomes	0.056	0.047	CI[0.0138, 0.1974]
Enjoyment			
RAs Specialization Degree → Choice Outcomes	0.063	0.118	
RAs Specialization Degree → Sense of Novelty	0.108	0.133	
Sense of Novelty → Choice Outcomes	0.758	0.051	
RAs Specialization Degree → Sense of Novelty → Choice Outcomes	0.082	0.072	CI[-0.042, 0.2829]
Satisfaction			
RAs Specialization Degree → Choice Outcomes	0.121	0.116	
RAs Specialization Degree → Sense of Novelty	0.108	0.133	*
Sense of Novelty → Choice Outcomes	0.466	0.051	***

RAs Specialization Degree → Sense of Novelty → Choice Outcomes	0.050	0.044	CI[0.0096, 0.1821]

Table 4. Direct and Indirect effects of RSs degree of novelty on choice outcomes and mediators

Discussion

Study 4 offers a solution algorithms' overspecialization by assessing the effectiveness of algorithmic novelty. The novelty is associated to higher choice outcomes and, hence, the H_5 is fully supported. Users tend to prefer RS able to provide them with novel products rather than RSs that are a mere reflection of their preferences. Novel products can be provided in many ways, through computation or a full novelty approach by randomly selecting products from the store. In accordance with the initial prediction, it is a way to form new preferences by discovering new items.

General Discussion

The current research investigated and tested the role of algorithms overspecialization in online marketplaces. I argued that RAs overspecialization is harmful for users' preferences and decreases the outcomes associated to the choice. A sequence of four studies supported the hypotheses. In different product categories, the increasing level of RAs accuracy is associated to lower levels of usefulness, willingness to adopt the RA, perceived benefit, enjoyment and satisfaction (Studies 1, 2 and 3). This effects are mitigated by the perceived reciprocity and intimacy (Study 2) and the enhancement of the breadth and depth of knowledge (Study 3). In contrast, the algorithmic novelty (i.e., the ability of the algorithm to provide items far from users' preferences) offers a viable solution to counteract the increasing RAs accuracy (Study 4).

This sequence of studies has several academic implications for the advice-taking literature. Focusing on transfer knowledge theory, I contrasted the prominent role of RAs accuracy assuming the users' perspective. Prior research has extensively discussed the benefits of algorithms' accuracy and has provided several evidence to build more accurate user profiles and improve RAs effectiveness without focusing on the drawback associated to the overspecialization (Song et al., 2019; Dzyabura et al., 2019; Isufi et al., 2021; Hamedani and

Kaedi, 2019; Panniello et al., 2014; Zhou et al., 2010; Ansari et al., 2000; Haübl et al., 2003; Knijnenburg et al., 2012; Lombardi et al., 2017; Tsekouras et al., 2020; Aggarwal. 2016). I proved that a decrease of the levels of recommendation accuracy results in more positive users' outcomes. It implies that higher levels of accuracy (i.e., overspecialization) undermine the evolution of users' preferences and that RAs should be able to create tailored experiences while offering the chance to encounter products far from extant preferences. This study provide contrasting evidence for theories that support the precision of RSs and shows that generalised information elicit people to think that the RSs is associated to higher outcomes.

The role of users' preferences are central to this article and discussed as the currency exchanged in the RAs-users relationship. However, RAs build accurate users' profile through the implicit elicitation of users' preferences and offer in return a RS. An interchange that does not allow user to distance themselves from the user profile. This drawback might result in a reduced ability of RAs to reciprocate and be perceived by users as a lack of reciprocity and intimacy (De Bruyn et al., 2020; Lee et al., 2017). A prominent reason for explaining such evidence is that people regard AI to be more similar to human beings than basic computers (Hoffman and Novak, 2018). Future study might look at this potential moderating effect. While extant literature has mainly focused on privacy concerns (Querci et al., 2022), I contribute to the understanding of such algorithm demonstrating that responses to accurate RAs may not be as positive since users perceive a lack of reciprocity and intimacy. Algorithm that allow them to enrich their preferences are seen as social actors more able to reciprocate and to be used as intimate friend. It implies that advice-taking literature should further consider the reciprocity and intimacy as a way to explain the outcomes towards RAs.

The current work, further contributes to the knowledge-transfer literature by assuming the user expertise as an antecedent of the rejection of overspecialization. When forming new expertise about products, consumers tend to leverage on the breadth and the depth of knowledge (D'Angelo and Valsesia, 2022). Tailored RSs do not amplify the breadth of knowledge while work on the depth of knowledge. Prior research, has partially highlighted that expert and non-expert individuals selected options far from their preferences in the half of cases without explaining the causes and the effects of this selection on choice's outcomes (Banker et al., 2019; Fitzsimons et al., 2004). I further explored this consistent selection of diverse products and found that users adopt RAs to amplify their breadth of knowledge rather than the depth. Oftentimes, RAs are meant as tools useful to expand the preferences and not narrowing them. As a result, RAs that improves the breadth of knowledge are associated to higher levels of outcomes than those working on the depth of knowledge. It implies that extant research should consider the ability of RAs to work on two different types of knowledge according to their degree of specialization a lead to different effects that can be further explored. One potential explanation to this finding is that users adopt RAs to develop new preferences.

Moreover, the current work proved that the novel RSs are a viable solution to overspecialization. Prior work has shown some methods to compute novelty mainly focusing on the degree of popularity of items without observing the need to find items far from users' preferences (Castells et al. 2011; Vargas and Castells 2011; Adamopoulos and Tuzhilin 2014; De Gemmis et al., 2015; McNee et al. 2006). Also, the extant literature has mainly focused on serendipity as a solution to RAs accuracy (Bao et al., 2022; Kim et al., 2021; Niu et al., 2021; Dzyabura et al., 2019; Grange et al., 2019; De Gemmis et al., 2015; Loeb et al., 2011) without considering that serendipitous feelings can be even favoured by overspecialization since are emotions that can also arise in conditions of familiar stimulus (i.e., the song in our memories that I are listening to after many years). The present research offers a different path by demonstrating the pivotal role of algorithmic novelty in online marketplaces to ensure the right balance between items close to users' preferences and others far from them. It has also implication on the journeys. Considering that user preferences vary over time, it would be more appropriate if the RA track a user's actions and interests over a longer period of time in order to find deviations from users' normal behaviour. RAs should always operate according to the follower approach already adopted to understand new users during their interactions with the e-tailer's eco-system. With users in the earliest stage of the journey, the RA tries to balance what is known and other random products to build an accurate user profile. Conversely, users on the loyalty stage reside in a loop according to RAs perspective without having the chance to distant themselves from their preferences. According to the results, the follower approach without an incessant maximization of the accuracy is the suggested approach that RAs should adopt.

Finally, the RA investigated in the research are common collaborative filtering adopted in the majority of online marketplaces and they are intended as tools able to provide users with items in line with their preferences (Ansari, 2000). They are changing the way marketers interact with users since are becoming a tool to get information about the assortment of a store. However, the implicit risks is an overfitting to the users preferences. While much of the existing literature has focused on addressing the accuracy problem, researcher must consider the decreasing efficacy of knowledgeable RAs on users' outcomes. This study broadens the research horizon by demonstrating that RAs are tools to expand users preferences and an increasing knowledge do not benefit users and their outcomes.

Practical implications

These findings also have relevant practical implications for marketers. Primarily, practitioners must focus on RAs that can enhance the items richness of RSs and provide users with balanced RSs formed to tailored recommendations and items that can nurture the users' preferences and the user profile. It can be pursued in two different ways, by reducing the knowledge about users or improving more sophisticated features that balance the accuracy with the generalisation. Since users frequently do not know or may not even hold a clear set of true preferences, the knowledge of RAs must not be predefined to offer merely a tailored RSs. It would be more appropriate to continuously nurture the user profiles with a the right attention to the degree of accuracy. In this way, users can benefit of different results and have the chance to enlarge their preferences. Indeed, the main effect of a overspecialised and knowledgeable RAs is the absence of the novelty, which is also an under researched RA feature which poses the solution to the overspecialization issue or filter bubble. There is a longstanding, and possibly misguided, belief that RAs can only execute activities based on their knowledge, such as the recommendation item. The topic becomes more complicated at this point, making it difficult yet essential to evaluate empirical data on the behaviour of algorithms and their effect of users. I proved that the integration of novel items in RSs lead to higher outcomes. Practitioners would benefit from a greater proposal of novel items in the RSs or, at least, a good balance between accurate and novel recommendations. Also, online marketplaces might disclose the level of knowledge or the number of interactions that led to a cumulated level of expertise about the user and give the chance to alter the paths computed by the algorithm by selecting generalised or tailored RAs. With a greater disclosure about the progress on the expertise formation, users would see the RAs as more beneficial and not as tools that want to tacitly invade the intimate sphere of users without a clear approval. By disclosing the level of RAs knowledge and its benefit, users might understand the aim of the tool to reciprocate and if they would opt for generalised RAs, they will be aware of the chances to form new preferences through new items. On the other side, RAs can increase their knowledge on users from a mutual exchange not limited to the provision of RSs. The enhancement of reciprocity can even lessen the increasing demand of data and allow practitioners to rely more on huma knowledge and not on predictive models. This is also beneficial to increase users' trust, control and reduce the locus in case of wrong recommendations (De Bruyn et al., 2020). If the RAs will continue to be programmed as optimizer of accuracy and architects of tacit knowledge, there will be a reduction of the outcomes towards their outputs.

Moreover, RAs design users' journeys according to their preferences. The implied risk in overspecialization settings is to align the RSs to users' expectations and limit their breadth of knowledge. The latter, thanks to the formation of new preferences, can even create a greater attachment towards the marketplace. In this perspective, alternative RSs can help users in their navigation. For instance, practitioners might reserve more sections for amplifying the breadth of knowledge and the depth by contemporarily leveraging on different levels of RAs specialization. It also has implications for the RAs networks. RAs are also based on consumption networks that link users to one other. RAs produce uniformity and a high level of similarity with the aim to combine users with similar interests and predict the preferences of those in the same clusters. However, the role of accurate gatekeepers is undermined by the need to form preferences and discover new items. By adapting the RSs only to preferred items, there would be and automatic effect on the overall efficacy of the system since the RA create more precise profiles and clusters of them but is limited in finding new patterns and intercept or predict new behaviours/similarities with users outside the clusters. Finally, there is the risk to undermine the customisation processes. With the aim to find a fit with the user profile, RAs might limit loyal customers to existing loops while new users are guided through predictive recommendations that are built according to users with similar interests. In these circumstances, the implicit risk is to guide the user towards a predicted journey rather than is own journey, based on real preferences. This risk is continuously nurtured if practitioners persevere on the improvement of RAs accuracy without finding the right balance between novelty and accuracy.

Limitations and future research

This article has a number of limitations which present opportunities for future research. First, I didn't focus on privacy concerns in Study 2. Future studies can further explore the results of the study by assessing the effects of privacy concerns related to RAs. Second, in Study 4

I mainly focused on novelty as a RA feature able to expand the number of never-seen products. Other type of novelty features can be explored, such as position novelty and its attempt to move the item in different sections of the page. The results of Study 3 suggest to investigate the differences between Novelty-seekers and routine-seeker in overspecialization context. Also, further product categories and degrees of product complexity can be assessed.

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Appendix 1 – Sample composition

	Study 1 *n=358*	Study 2 *n=304*	Study 3 *n=362*	Study 4 *n=301*
Gender				
Male	50.0	33.0	50.0	49.5
Female	49.4	65.7	49.2	50.2
Prefer not to say	0.6	1.3	0.8	0.3
Age				
18-24	1.1	0.0	0.0	13.0
25-34	68.7	25.7	58.3	52.2
35-44	17.3	66.1	27.3	20.9
45-54	8.9	0.0	4.4	9.3
55-64	2.8	0.0	0.0	3.3
65+	1.1	0.0	0.0	1.3
Income				
Less than $10,000	36.0	36.1	21.0	27.2
€10,000 - €19,999	26.5	27.0	27.6	22.9
€20,000 - €39,999	22.3	20.9	27.6	30.9
€40,000 - €59,999	9.2	8.3	15.2	12.3
€60,000 - €89,999	4.5	4.8	3.9	4.3
€90,000 - €99,999	0.6	2.2	3.0	1.3
More than €100,000	0.8	0.9	1.7	1.0
Education				
Less than high school	0.6	0.4	0.0	1.0
High school graduate	17.6	20.0	13.0	16.3
College/Bachelor or equivalent	52.0	57.0	51.7	52.5
Master of Science/ Master of Arts or equivalent	27.9	21.3	33.7	27.2
Doctorate	2.0	1.3	1.7	3.0

Conclusions

In the sequence of the studies, I discussed (i) the effects of Recommendation Agents (RAs) on consumer decision-making process, (ii) their ability to generate implicit social networks and (iii) investigated how increasing levels of RAs accuracy are associated to lower levels of usefulness, willingness to adopt the RA, perceived benefit, enjoyment and satisfaction. The findings are relevant for different purposes and propose important theoretical and practical implications. From a theoretical standpoint, the first article is an organization of the extant literature in three main theoretical background. It aimed to provide a systematization of the extant articles and highlight the main research gaps. Although some topics have been clarified and explained in detail, to date there are still many questions about the effectiveness of RAs. The in-depth review of the literature has led me to highlight 10 gaps as foundations for future research mainly referred to: (i) the lack of investigations of some type of RAs, (ii) some features are still under researched such as *novelty*, *serendipity* and *diversity* of RAs – two of them have been investigated, after 3 years, in Chapter III; (iii) the absence of a unique acceptance model for algorithms; (iv) how they affect the different stages of the costumer journey – addressed in Chapter II; (v) a lack of contributions on the methods of presenting the explanations; (vi) contributions related to different rewarding methods for users are yet missing; (vii) no studies explain the social relationships that are established between algorithms placed at the service of the user and the user himself; (viii) the presence of qualitative studies or alternative approaches is restricted; (ix) an additional point concerns the possible differences that may exist in relation to specific categories of users; (x) no contributions are made in relation to recommendations based on spatial or temporal proximity.

All the previous points laid down the foundations for the second chapter in which I argued, that networks enabled by RAs, that aim to combine users in neighbourhoods according to their preferences, can be compared to other networks investigated in the past and under the lenses of the theory of the strength of weak ties (Granovetter, 1973). I found that users which rely on weak ties within the neighborhood are those that are more likely to convey recommendations through several neighbourhoods and to wide spread a marketing message after the purchase, whereas strong-tie consumers are more likely to mainly convey messages within their own communities. Such bridge users, with weak ties, a peripheral position in the community and a central role in the network, have been discussed in other studies for their ability to bring an information from the external context to the internal environment (Vikatos et al. 2020, Corradini et al. 2020, Granovetter, 1973; Burt, 1992; White, 1970). Those users characterized by short distances with others and often resides in the middle way between two other users are more likely to spread the recommendation. These two measures, under conditions of the existence of neighbourhoods document that those who are highly embedded in a community cannot rely on central positions of the main network since their connections mainly refer to the members of the community itself, which is a subnetwork of the main structure. Conversely, those who share links with members of different communities, tie with a large numbers of users disseminated in the network.

More generally, the findings suggest that RAs implicit networks are composed by different users neighbourhoods which rely on a gradient of recommendation dissemination that varies according to the embeddedness of the users in a community, the centrality and connections with relevant other users of a neighborhood. Those who are less connected in a community, widespread the information across different neighborhood, while highly-connected users tend to spread the recommendation in their community. It means that, well-connected members of a community are more likely to deliver the communication only within the community, while weak-ties users to reach their neighborhood and the others.

However, this fact led me to conceive the third study. Does the algorithm specialization really benefit the consumers? Do they prefer specialized RAs (which confine them inside their neighbourhoods) or RAs able to provide novel and serendipitous elements?

In the Chapter III, I found the answer to this questions, by proving that a decrease of the levels of recommendation accuracy results in more positive users' outcomes. It implies that higher levels of accuracy (i.e., overspecialization) undermine the evolution of users' preferences and that RAs should be able to create tailored experiences while offering the chance to encounter products far from extant preferences – outside the neighbourhood. An evidence that contrasts theories that support the precision of RAs and shows that generalised information elicit people to think that the RAs is associated to higher outcomes . However, RAs build accurate users' profile through the implicit elicitation of users' preferences and offer in return a recommendation set. An interchange that does not allow user to distance themselves from the user profile. This drawback might result in a reduced ability of RAs to reciprocate and be perceived by users as a lack of reciprocity and intimacy (De Bruyn et al., 2020; Lee et al., 2017). Chapter III has also offered a different path by demonstrating the pivotal role of algorithmic novelty in online marketplaces to ensure the right balance between items close to users' preferences and others far from them.

The present work contributes to extant marketing literature in three ways: (i) by providing an updated systematic literature review on the topic and explained the effect of RAs on consumers; (ii) describing how today users are implicitly linked to people with the same preferences, in other part of the world, and exposed to the same recommendation due to the shared preferences in a multitude of social networks created implicitly and used to accommodate and predict our request; (iii) the specialization of such RAs that leads to higher levels of knowledge about the users is not always well perceived by themselves. They tend to prefer RAs able to diversify the recommendation set with items far from their preferences and that, in turn, can extend (and not limit) their actual preferences.

In conclusion, RAs are effective tools to affect consumer responses in digital environment thanks to their ability to mimic word-of-mouth and generate neighbourhood of costumers with similar preferences. However, their effectiveness is limited by the need of consumer to extend their preferences beyond the actual ones. It indeed generates a paradox in which RAs tend to predict consumers' choices by monitoring and associating them to group of similar users and, on the other hand, consumers expect to see products even far from their preferences and extend their actual knowledge in make new discoveries. If RAs will progressively decentralize central nodes and move them towards the periphery of the neighborhood, consumers will benefit of novel and serendipitous items and response with more positive outcomes towards the recommendation set and the e-tailer.