

Jansen, Thomas; Moura, Francisco Tigre

**Working Paper**

## WOM, eWOM and WOMachine: The evolution of consumer recommendations through a systematic review of 194 studies

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# IU DISCUSSION

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WOM, eWOM and WOMachine: The Evolution of Consumer Recommendations Through a Systematic Review Of 194 Studies.

**THOMAS JANSEN**

**FRANCISCO TIGRE MOURA**

**IU Internationale Hochschule**

Main Campus: Erfurt  
Juri-Gagarin-Ring 152  
99084 Erfurt

Telefon: +49 421.166985.23

Fax: +49 2224.9605.115

Kontakt/Contact: [kerstin.janson@iu.org](mailto:kerstin.janson@iu.org)

Contact to the author:

Thomas Jansen

ORCID-ID: 0000-0003-2636-1499

IU Internationale Hochschule - Campus Bad Honnef

Mülheimer Str. 38

Bad Honnef 53604

Email: [thomas.jansen@iubh.de](mailto:thomas.jansen@iubh.de)

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# **WOM, eWOM and WOMachine:**

## **The Evolution of Consumer Recommendations Through a Systematic Review Of 194 Studies.**

**Thomas Jansen**

**Francisco Tigre Moura**

### **ABSTRACT:**

*Recommendation-based communication plays a pivotal role in consumer choices. From human sources to electronic word of mouth or different types of recommender systems, recommendations help consumers adopt or reject leads, and can be highly beneficial for organizations. In view of its relevance and the distinct characteristics the evolution of the topic, this paper aims to identify, summarize, and analyze the developments and impact of these recommendations on consumer decision making. To achieve this, 194 evidence-based studies were systematically reviewed. The results from a thematic synthesis showed that eWOM and recommender systems have a synergistic effect fueled by non-verbal cues of eWOM and accuracy of the system. Conversational recommender systems act similarly to WOM by encouraging explicit feedback. However, data privacy concerns make interactions towards these systems a difficult matter. Themes that emerged from WOM emphasized interpersonal relationships that are homophilous and with strong ties. Themes from eWOM focused on volume as a cue for popularity which increased credibility and trustworthiness. Finally, themes for automated recommendation center on usefulness and anthropomorphizing the recommender to build trust. Implications and future directions are provided.*

### **KEYWORDS:**

*WOM, eWOM, WOMachine, Recommender Systems, Conversational Recommender System.*

**JEL Classification: M31 (Marketing).**

### **AUTHORS**



**Thomas Jansen** Thomas Jansen is an alumnus of IU International University of Applied Sciences. He graduated with a degree in International Management and is currently engaged in a funding institution which aims at making higher education possible for qualified individuals regardless of their financial circumstances.



**Prof. Dr. Francisco Tigre Moura** holds a PhD in Marketing from the University of Otago (New Zealand) and has worked since 2013 as Professor of Marketing at IU International University of Applied Sciences, Germany. Research interests include creativity and artificial creativity, sustainable consumption, and technology experiences in the entertainment sector. He is the founder of LiveInnovation.org, a research and education website which, among other topics, discusses technology innovation in the entertainment sector.

## 1. Introduction

Recommendation-based communication is complex, multidimensional, and has been largely researched due to its vital role in consumers' decision-making process. Along history, it has been extended from human-to-human interactions, to human-computer interactions, and most recently, in the emerging field of human-AI interactions (Amershi et al., 2019).

The discussions involving Word-of-Mouth (WOM) communication and its impact on consumer choices starts with the pioneering work of Arndt (1967), who brought light into how product related conversations lead to its spread and consequently, purchase behavior. Since then, numerous scholars have researched human to human WOM communication from a pre-Internet setting, up to the present day which continues to be just as relevant as before (Amani, 2022).

As the internet popularized and new technologies during the Web 2.0 were created, there was a shift in how consumers use WOM communication, opening a new field of possibilities. This paved the way for online WOM or electronic word-of-mouth communication (eWOM) (Hennig-Thurau et al., 2004). The combination of multiple transmissions, indefinite availability to consumers, and anonymity provided by eWOM communication has resulted to profound effects in consumer behavior, specifically product judgements and willingness to recommend (M. Lee & Youn, 2009). Today's constant surge of information has made eWOM an inseparable part of consumers' lives through social media posts, blogs, vlogs, and online reviews (Moran & Muzellec, 2017).

While eWOM and WOM are fundamental sources of human-based recommendations, the extraction, analysis and application of individual and collective consumer data for recommendations has recently become the basis of the data driven economy (Braverman, 2015). Recommender systems, also called recommendation agents, began gaining traction in the early 90s as a solution to filter the vast amounts of unwanted content (Huttner, 2009). Since then, the popularity and efficiency of recommender systems has increased in sites such as Netflix, Amazon, YouTube, TripAdvisor and many more. Furthermore, progress in artificial intelligence, human-computer interaction, and information retrieval have played a pivotal role in the development of recommender systems (Sharma & Singh, 2016).

Thus, in view of the unquestionable relevance and influence of WOM, eWOM and automated recommendations to consumers' decision-making, and the unique characteristics of each stage, this paper aims to provide a systematic review of evidence-based studies that focused on each stage of recommendations. And thus, allow.

## 2. The evolution of recommendations: from Word of Mouth (WOM) to Electronic Word of Mouth (eWOM), to Automated Recommendations.

### 2.1 WORD OF MOUTH (WOM)

Despite the multiple definitions in the current literature, Ismagilova et al. (2017) describes WOM as an "oral, person-to-person communication between a receiver and a communicator, whom the receiver perceives as non-commercial, concerning a brand, product, service, or organization" (Ismagilova et al., 2017, p.7). One of the earliest references to WOM in marketing is from Brooks (1957), wherein it was

acknowledged that advertising and personal selling were not the only sources of information about products for consumers.

There are four major motives to engage in WOM communication, to aid in reducing cognitive dissonance, to be perceived as well-informed, and for altruistic purposes (Arndt, 1967a). Lastly, tie strength also dictates the influence in which WOM is transmitted (Granovetter, 1973; J. J. Brown & Reingen, 1987). Strong ties, for instance coming from family or friends, more frequently engage in WOM communications than those of weak ties like acquaintances (Wirtz & Chew, 2002). A recommendation can come across as compelling when the receiver perceives the sender or reference group to be credible and trustworthy (Bearden et al., 1989; Bearden & Etzel, 1982). Moreover, in relation to tie strength, information coming from strong ties is seen as more trustworthy than those coming from weak ties (Bansal & Voyer, 2000). Second, on the receiver's side, we look at their expertise.

Consequently, WOM communication has various impacts on consumer behaviour (Buttle, 1998). A recommendation can change the attitude towards various products and services, for instance, computers (Herr et al., 1991), motion pictures (Burzynski & Bayer, 1977), and food (Bone, 1995). Interestingly, when it comes to new products and ideas, WOM becomes a vital part in the adoption of innovation due to consumer doubts and reservations (Engel, 1969). Ultimately, purchase intention, plays a crucial role as an outcome of WOM communication and remains to be an indispensable variable in marketing research (Arndt, 1967b; Bansal & Voyer, 2000).

## **2.2 ELECTRONIC WORD OF MOUTH (eWOM)**

eWOM is commonly known as “any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the internet” (Hennig-Thurau et al., 2004, p. 39). As the internet became mainstream, the general public quickly became the “media” itself through sharing information on multiple online platforms (Li & Wang, 2011). Web 2.0 platforms allowed one to one, one to many, many to one, and many to many communications which make eWOM a dynamic process of information exchanges (Weisfeld-Spolter et al., 2014; Xun & Reynolds, 2010). Additionally, eWOM also includes the increasing prevalence of neutral content (Kietzmann & Canhoto, 2013).

Furthermore, the level of satisfaction in both cognitive and emotional aspects are reason for the spread of eWOM (De Matos & Rossi, 2008). When the expectations are exceeded, consumers are motivated to share their positive experiences meanwhile, when they are not met, dissatisfaction occurs, and they share to alleviate negative emotions. Second, loyalty-- when consumers stay with the product or service provider through repeat purchases or with an intent to do the same (Sirdeshmukh et al., 2002). Such behaviours' aftereffects are manifested in friend referrals since there is a heightened social image risk the referrer is taking, therefore loyalty is needed (Reichheld, 1993). The third antecedent which is commitment is focused on the desired relationship between consumer and organization (Morgan & Hunt, 1994).

Similar to WOM, receivers use eWOM for risk reduction. Uncertainty lessens as interpersonal information provides clarity and builds trust and confidence in pre-purchase situations (Silverman, 2011) and the difficulty of considering all alternatives is lessened when engaging in eWOM (Han, 2008).

## **2.3 AUTOMATED RECOMMENDATIONS**

The rapid advancement of information and communications technology has not only enabled widespread dissemination of information but also an ongoing sophistication of automated sources of

information, for instance, recommender systems. Recommender systems are software tools that aid in the decision-making process by suggesting items that are of interest to the consumer (Resnick & Varian, 1997).

Some of the approaches used for machine learning algorithms used in recommender systems include content-based, collaborative filtering, demographic, knowledge based, and hybrid recommender systems (Burke, 2007). Such approaches have become widely implemented by companies such as Amazon, LinkedIn, Facebook, Spotify, Twitter, and Google (Ricci et al., 2015).

The rationales for using recommender systems are plentiful for both providers and users. In addition to the commercial reason of having more items sold or higher conversion rate, the recommender system nudges users into selecting more diverse items (Borràs et al., 2014).

On the users' side, recommender systems assist in filtering the enormous amounts of information and avoiding choice overload (or the paradox of choice). The application areas go beyond just having to look for a specific product to purchase as is the case with e-commerce, but it extends to different areas; these can be for entertainment such as movies, games, and music, for services such as travel, medical, or other expert consultations, and for social purposes on SNS (Montaner et al., 2003). In cases where the options are not as plenty and the decisions to make are vital to the user, for instance, medical or financial purposes, it is all the more important for the recommender system to provide the best information possible and therefore, seek credibility (Ricci et al., 2015).

Such algorithm have a powerful impact on choices of consumers as they predict the intentions of users by working in the background whilst being fed large amounts of data which can possibly be “noisy” and deemed impractical in real applications of dynamic interactions (Shi et al., 2014).

### 3. Methodology

#### 3.1 SEARCH STRATEGY

Databases that were used are EBSCO Business Source Ultimate, Emerald, IEEE Xplore and Google Scholar. Keywords were separated between human-based and automated recommendations. Examples include: “eWOM recommendations”, “WOM recommendations”, and “Recommendation perception” (human based), and “AI recommendations”, “Recommender systems”, “Conversational recommender systems”, and “Chatbot recommendation perception” (automated recommendations). In addition, Boolean operators were used to refine the search (e.g., ‘AND’ and ‘OR’). Furthermore, complementary search tasks were implemented throughout the search process, such as citation chaining, including backward searching and forward searching (Boland et al. 2017). The main search took place in March 2022.

#### 3.2 INCLUSION AND EXCLUSION CRITERIA

For the purpose of this review, the authors defined the following inclusion criteria: (a) paper must be empirical which provides evidence of primary data collection with analysis and conclusion; (b) there must be content that is recommended which falls under the products and/or services category; (c) the content recommended must originate from a distinct source, meaning from a person, group, company, or an automated entity; (d) the aim of each paper puts emphasis on the evaluation of the recommendation and its corresponding effects coming from it (e) findings from the studies are relevant

to consumer decision making, and (f) comparative studies which analyze differences within the human (automated) recommendations or cross comparisons with automated (human) recommendations.

Furthermore, the following additional exclusion criteria were also adopted: (a) papers where the end effect is WOM or eWOM spread. This is especially important as the investigation must be where WOM or eWOM is within the process or the cause of an effect being measured. (b) papers that only concentrate on the motives for engaging in recommendation-based communication; (c) for automated sources, papers where the role of the source lean towards customer service (e.g., a consumer uses a chatbot for complaint management or a virtual assistant to book hotels and flights); (d) papers where the results are purely conversion rates or sales and do not elaborate on the inner workings of consumer decision making. The inclusion and exclusion criteria are summarized in Table 1 below.

Inclusion Criteria	Exclusion Criteria
1. Empirical Studies	1. Act of recommending is an end result
2. Includes product/service recommendation	2. Studies concentrated on motives for recommending
3. Recommendations comes from distinct source	3. Automated sources that lack clear recommending capabilities
4. Evaluation of recommendation is discussed	4. Performance based studies that do not elaborate on inner workings of recommendation-based communication
5. Relevance to consumer decision making	
6. Comparative studies between automated and human recommendations	

Table 1: Summary of inclusion and exclusion criteria for the review.

### 3.3 SCREENING AND SELECTION

To ensure transparency, the screening process is shown in Figure 1 through a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram, which represents the flow of information (Page et al., 2021).



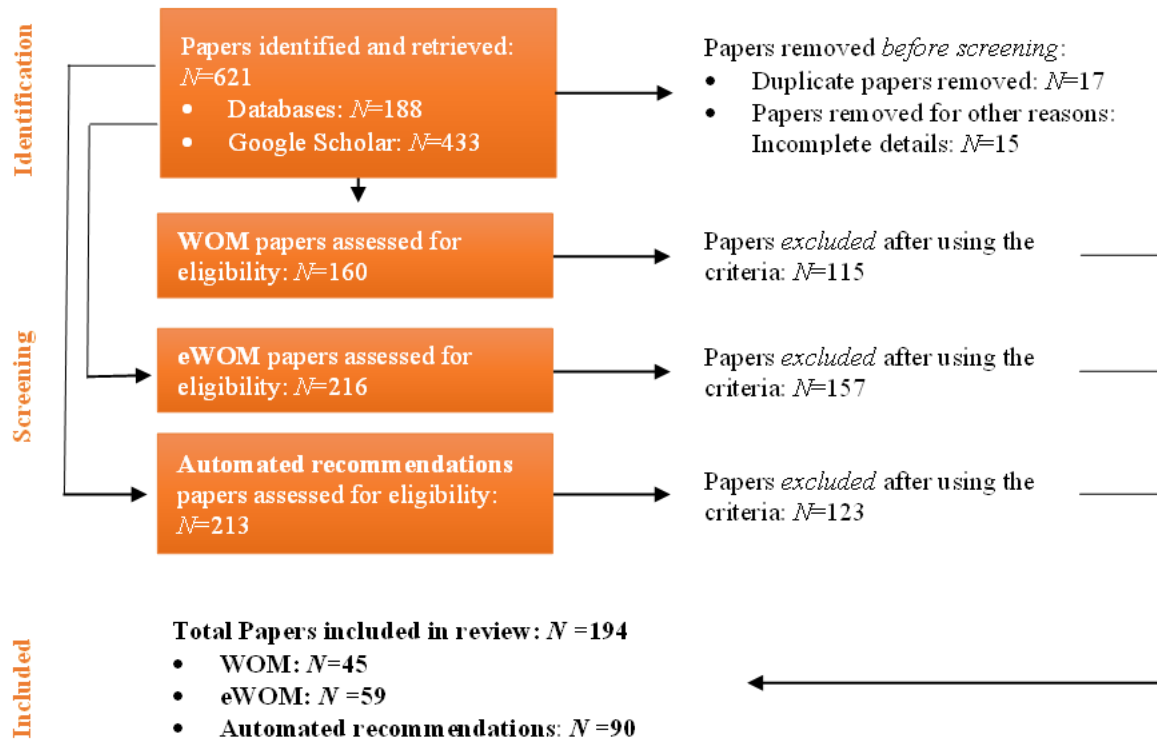


Figure 1: PRISMA Flow Diagram (Adapted and Modified from Page et al., 2021, p. 5).

As noted, from the initial 621 papers collected, 32 duplicate papers (or with incomplete details) were removed before the screening and selection process. Following the inclusion and exclusion criteria, 68.76% of all 621 papers collected initially were excluded. Thus, the final sample included in the systematic review consisted of 194 papers (WOM=45; eWOM=59; Automated recommendations=90).

### 3.4 DATA EXTRACTION AND QUALITY ASSESSMENT

The summarization of the studies contained seven categories of analysis: (a) Author/s and Year; (b) Content Recommended (Products and Services); (c) Study Aim; (d) Sample; (e) Method/s; (f) Codes for Analysis; and (g) Findings. The seven categories are included in each of the three review tables for WOM, eWOM, and Automated recommendations, in the appendix of this paper for data consolidation. The first five categories consist of descriptive data extracted while the last two categories consist of the analytical data that has been extracted. The development of such categories was derived from previous systematic reviews (Tigre Moura et al., 2016), discussions with scholars for relevance and suitability for the aim of the paper.

According to Khan et al. (2003), quality refers to the extent to which a study's design, conduct, and analysis include steps to reduce bias and error. Needless to say, peer reviewed academic journals are central to establishing quality and legitimacy of research in their respective disciplines (Tennant & Ross-Hellauer, 2020). Majority of the quality assessment happened before data extraction and, thus, during the review of the papers in unison with the application of the inclusion and exclusion criteria.

### 3.5 SYNTHESIS AND ANALYSIS

The first approach to synthesizing the studies was the integrative synthesis, which takes a deductive approach. Thus, categories or concepts are already well defined; the primary studies that provide the data are precisely comparable to each other and are fit for aggregation (Boland et al., 2017). The second approach was the interpretative synthesis which takes an inductive approach, wherein categories or concepts were not predetermined but it is the aim to develop these along the process of synthesizing the included studies (Boland et al., 2017). Accordingly, to synthesize the included studies in this systematic review, the interpretative way was taken. Nonetheless, the two ways of synthesis are not always distinct from each other as interpretation may contain elements of integration and vice versa (Lockwood et al., 2015). Furthermore, to analyze the qualitative data coming from the included studies, the systematic review also employed principles from thematic analysis. A method which is foremost used to analyze primary qualitative research, it can also be transferred to analyze secondary data i.e., findings of multiple studies of a systematic review; researchers also call this “thematic synthesis” (Thomas & Harden, 2008).

## 4. Findings and Discussion

As mentioned previously, the aim of this paper is to identify, analyze and summarize the developments and impact of human-human, human-machine and automated recommendations on consumer decision making. To fulfill this aim, the findings are separated into two parts.

The first part presents the descriptive data of the systematic review while the second part discusses the analytical data.

### 4.1 DESCRIPTIVE FINDINGS

First, Figure 2 provides an important overview of the included studies throughout the years. The frequency of the studies in their respective automated and human-based recommendations classification is presented by decade with an exception for years 2021 and 2022 in Figure 2.

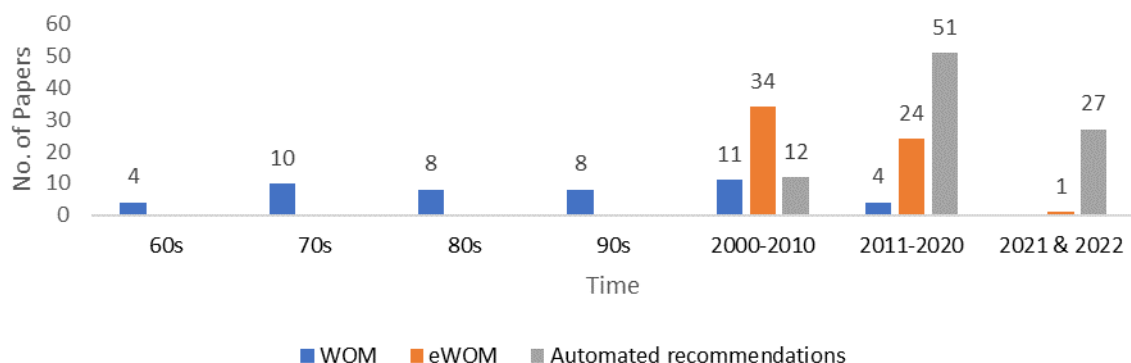


Figure 2: Historical Overview of Empirical Studies Involving Recommendations

As evidenced in the figure, WOM studies have remained stable since the 60s, which showed an even distribution of studies by decade with no remarkable spike that can be observed. WOM studies in its traditional definition i.e., face-to-face, became less popular after 2010 as researchers have used WOM and eWOM interchangeably, while interactions in consideration to the online setting has become

inevitable. In relation to eWOM studies, a spike is observed in the first decade of 2000 as the internet has become mainstream.

As for automated recommendations, a spike in studies can be seen in the decade 2011-2020 as CRS have started flourishing and the continuous sophistication of recommender systems. It must be noted that, the decreasing number of studies for eWOM is no indication for its decline as these are just papers that have passed the criteria for the review. Plenty of studies involving eWOM are available up until 2022 albeit, at a scope beyond this review.

Regarding the type of “Content Recommended” (Products and/or services) being recommended based on the different recommendation-based communication, Figure 3 reveals that papers that studied WOM are predominantly focused on tangible products (68% of the total studies included). A possible reason behind this discrepancy is the adherence to the earliest understanding of WOM as a “product-related conversation” among consumers (Arndt, 1967b). The majority of the WOM papers have focused on household items especially, the early studies. Services have come later as conversations are naturally, not confined in a product only context.

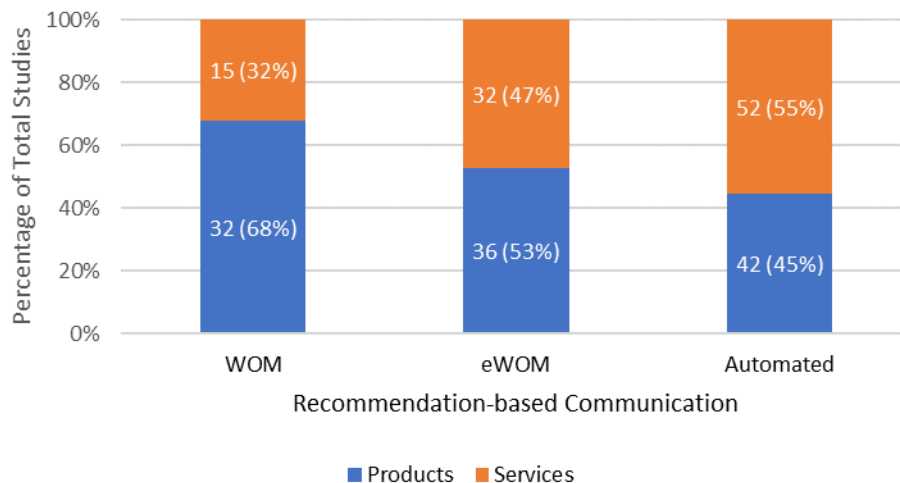


Figure 3: Distribution of Content Recommended

On the other hand, one can observe a more even distribution between products and services for eWOM studies. The increased popularity of e-commerce has made recommending products mainstream. The tourism and hospitality sector going online have propelled the service recommendation studies for eWOM as well. As might be expected, discussion forums cover a wide range of products and services; companies have their own reviews section which made eWOM studies diversified in their investigations of content recommendation. For automated recommendations, a clear difference between products and services cannot be discerned. And importantly, it is possible that a single study investigates multiple products and services. Moreover, a paper with multiple studies can also investigate a single product or service recommendation.

The category “Method/s” examined the different methods used in each recommendation-based communication. In total, there were five main methods identified and summarized in their different classifications, which is presented in Figure 4.

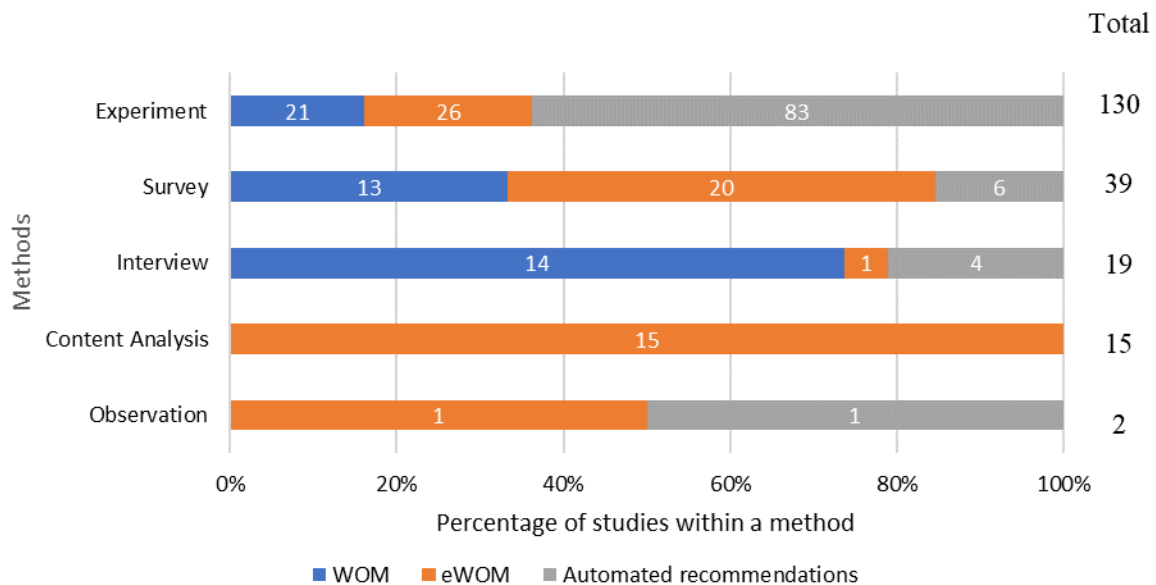


Figure 4: Distribution of Methods used.

With a considerable margin compared to other methods, totaling 130, experimental studies are the most used among all. It is also the most used method in both automated and human-based recommendations. It should be mentioned that almost all the experimental studies used a between-subjects design and randomly choosing respondents into groups with different conditions. To a large extent, automated recommendations have the majority with 83 experimental studies. It seems to be essential for recommender systems and CRS to be tested using different manipulations and analyze its effects on the consumer. The second most used method are surveys for eWOM and automated recommendation. It is also apparent that, there is not a large difference for methods used regarding experiments and surveys for eWOM studies, unlike that of automated recommendation studies which seem to have preference for experiments. For interviews, most of its usage is for WOM studies. It is possible that this has to do with the face-to-face nature of WOM and it could be a method wherein the validity of the results can be strengthened. Content analysis, on the other hand, is exclusively reserved for eWOM studies. This comes to no surprise as the enormous number of reviews online are readily available data that can be analyzed. Different platforms or websites give various contexts for eWOM to be studied. The least used method is observation with only two studies split between eWOM and automated recommendations. WOM studies did not utilize observation, which could have been caused by the difficulty of implementing the said method. Observing consumers in a natural setting involving WOM can be a costly task due to time and may spark privacy concerns among respondents conversing face-to-face about products and services.

## 4.2 DISCUSSION

The analysis will be presented next by discussing the source, message, receiver, and interpersonal factors relating to automated and human-based recommendations. Furthermore, themes that emerged from synthesizing the findings of the studies are discussed.

### 4.2.1 WOM

In WOM communication, an ideal source is someone who has credibility, reliability, expertise, and is trustworthy (Asada & Ko, 2016; Mookerjee, 2001). The influence of opinion leaders is powerful in WOM communication. They are highly involved in disseminating WOM in the pre-decision phases of consumers (Summers, 1970). They are a definitive figure at the phase where a decision has to be made rather than in the introduction phases of information seeking (Martilla, 1971). The effect they have are enduring when giving advice which means they are especially important for decision makers considering long term effects of a purchase; short term considerations are affected as well by sharing own experiences (Richins & Root-Shaffer, 1988). Opinion leaders are influential even in groups where beliefs may vary, group decisions will be made based on the word of the opinion leader (Shaw et al., 2005). The problem with opinion leaders is, they can slow down innovation or the diffusion of innovation because they are strongly tied to what they believe in, rendering them ineffective to early adapters who shifted their credibility demands to other sources (Leonard-Barton, 1985). Market mavens, on the other hand, are experts in certain areas and hold information that may be valuable for a lot of people. They diffuse information more often than the average consumer (Higie et al., 1987). Personal sources are sought more when higher risks are involved and for later stages of the information seeking process (Berning & Jacoby, 1974; J. N. Sheth & Venkatesan, 1968). Conversely, external sources are sought for their objective knowledge because they are not in personal contact to the consumer (Mattila & Wirtz, 2002).

The valence, specifically negative valence of the message has an overarching importance. Negative WOM has a greater impact than positive WOM on brand attitude and cognitive structure of the consumer (Lutz, 1975). Furthermore, negative ratings have strong attributions to product performance, belief strength, and emotions or affect; negative WOM are seen as more credible (Mizerski, 1982). The impact of negative WOM is seen as more significant for services, it has a strong effect on behavioral intention, and is influential (Y. Chen et al., 2011; Hou Wee et al., 1995; Weinberger & Dillon, 1980). Contrarily, positive WOM is effective when the consumer is highly involved in the product category in general (Giese et al., 1996). Although positive WOM occur more often than negative WOM, they both have the same impact when it comes to the purchase stages (East et al., 2005). Ultimately, even two-sided messages have a stronger impact in making consumers purchase than purely positive WOM (Hou Wee et al., 1995). In other aspects outside valence, Delgadillo & Escalas (2004) have argued that WOM is generally structured as a narrative which can be a biased memory of the story details because of recall of story gist. Vividness of the recommendation makes the information more interesting, attention drawing, and thought provoking which help with evaluations for the consumer (Herr et al., 1991). Interestingly, when the message is diagnostic, meaning the alternatives are easily distinguished it is highly effective; diagnostic messages from non-experts are more effective than non-diagnostic messages from experts (Hansen & Singh, 2009).

The strong effect of WOM is moderated when the receiver already has prior evaluation, impression, self-assessed knowledge, and is not that involved (Asada & Ko, 2016; Herr et al., 1991; Mattila & Wirtz, 2002; Wilson & Peterson, 1989). The effect of WOM can even backlash when it is unsolicited and contradicts with initial impressions; this leads to ignoring the recommendation or intentionally going against it (Fitzsimons & Lehmann, 2004). The interpersonal relationship between the source and receiver plays a role in WOM communication. A recommendation is especially effective when the relationship is homophilous (similar minded) and the tie between them is strong (J. J. Brown & Reingen, 1987). A homophilous relationship is especially important when there are numerous differences in the alternatives (Feick & Higie, 1992). Homophily boosted the effect of negative WOM and also acts as a moderating factor in the strength of WOM (Asada & Ko, 2016; Sweeney et al., 2014). If the WOM is seeded,

it is effective for weak ties, and effective for strong ties as long as part of the reward goes to the receiver (Ryu & Feick, 2007). Friends who received a reward were perceived as less sincere when communicating WOM, although recommendation is still willingly adopted regardless of incentives (Tuk, 2008). In fact, a close tie relationship in WOM communication is still effective even when presented by a non-expert telling non-specific information (Cox & Repede, 2013).

Author and Year	Content Recommended (Products and Services)	Study Aim	Sample	Method/s	Codes for Analysis	Findings
(Chatterjee, 2001)	Course Textbook	Explain initial online review usage in the context of retailers	419	Experiment	Message, Receiver	The extent of eWOM search is dependent on why the consumer chose online retailer. Negative eWOM effect on perceived reliability and purchase intention is dependent on familiarity with retailer and if it is pure internet or clicks and mortar
(Schlosser, 2005)	Movie	Investigate source perceptions and persuasiveness of eWOM	125	Experiments	Message	Two-sided messages do not always mean more credibility, if brand attitude is extreme, it can even be less credible than one sided message.
(E.-Y. Lee et al., 2005)	Online shopping products and services (not specified)	Investigate effect of information characteristics on eWOM performance and consumer knowledge as a moderator	293	Survey	Message, Receiver	Consumer knowledge has a moderating role in the relationship between information characteristics and WOM performance
(Fong & Burton, 2006)	Digital Camera	Extent of eWOM on different websites from US and China	3243	Survey and Observation	Receiver	US based participants relatively provide more sources of information in comparison to information requests
(Y. Liu, 2006)	Movies	Dynamics and impact of eWOM on Box office Revenues	40	Content Analysis	Message	From the 12,136 eWOM messages analyzed, box office revenues can be explained by volume and not valence of the messages. The percentage of positive and negative messages were measured
(Gruen et al., 2006)	Video editing software	Investigate the influence of eWOM in form of know-how exchange on product value perception and loyalty intentions	616	Survey	Receiver	eWOM exchange impacts product value perceptions and likelihood of recommending
(Amblee & Bui, 2007a)	Digital Photo Tools	The influence of two forms of eWOM on the number of downloads: those produced by experts (professional reviewers) and those supplied by users (consumers).	143	Content Analysis	Source, Message	In terms of relevance and importance, both forms of eWOM have similar effects. Additionally, valence does not matter
(Amblee & Bui, 2007b)	Digital Microproducts (short books)	Impact of eWOM on the sale of digital microproducts	551	Content Analysis	Message	Ratings are not a good predictor for book sales. Volume of reviews and reputation of complementary goods are correlated to book sales
(M. Y. Cheung et al., 2007)	Discussion Forum (various products and services)	The role of Informational and Normative Based Determinants of perceived credibility in evaluating eWOM	159	Survey	Source, Message, Receiver	Source credibility, argument strength, and receiver's confirmation with prior beliefs (informational determinants) and eWOM consistency and rating (normative determinants) are salient in credibility evaluation of eWOM

(D.-H. Park et al., 2007)	Portable multimedia player	The moderating role of level of involvement in the relationship between volume and quality of eWOM	252	Experiment	Message, Receiver	Purchase intentions are positively influenced by the quality of eWOM. Purchasing intention rises as the volume rises, and low-involvement customers are more impacted by volume than by eWOM quality, but high-involvement consumers are primarily affected by volume only when eWOM quality is high.
(X. Wang et al., 2007)	Hotels	Identify factors that aid in the acceptance of eWOM	341	Experiment	Source	Sender expertise and trustworthiness were critical in diagnosing eWOM acceptance. Helpfulness and status are indicators which have an effect on acceptance or rejection
(Duan et al., 2008)	Movies	Investigation of the dynamics of eWOM and sales in the context of the movie industry	71	Content Analysis	Message	Box office revenue and eWOM valence impact eWOM volume which in turn lead to higher performance of box office
(A. Davis & Khazanchi, 2008)	Multiple products categories	Impact of eWOM attributes and other factors on sales	328	Content Analysis	Message	The interaction of category of the product, eWOM volume, and views are significant in the change of sales. High volume itself has no significance on sales
(Harris & Gupta, 2008)	Notebook computers	Investigate the impact of eWOM on attitudes about the recommended product and confidence in the decision	120	Experiment	Message, Receiver	The volume of eWOM has significant impact in the confidence of their choice. The choice confidence of consumers who are less motivated to process eWOM is mediated by their attitude towards the recommended product. Ergo, volume of eWOM acts as a purchase cue
(House et al., 2008)	Candy bar, Sandwich, and Meal	Explore whether factors representing various features of group structure may better explain consumers acceptance of new food products	380	Survey	Source, Receiver	Both the receiver and the sender's network position have an impact. Furthermore, depending on the food product investigated, the qualities that influence propensity to listen to the recommendation differ.
(Casaló et al., 2008)	e-banking services	Characterize customer loyalty and positive eWOM in the e-banking context	142	Survey	Message	Positive eWOM paired with website usability led to customer satisfaction and loyalty
(J. Lee et al., 2008)	MP3 Player	Investigate the impact of negative eWOM on consumer attitude	248	Experiment	Message, Receiver	High volume of negative eWOM tends to make high involvement consumers conform to them depending on the quality of the negative review. Low involvement consumers conform regardless of the quality of the review.
(D.-H. Park & Kim, 2008)	Portable multimedia player	Effect of cognitive fit (review type) and volume on purchase intention of consumers in relation to their level of expertise	222	Experiment	Message, Receiver	Cognitive fit (review type) (attribute-centric vs. benefit-centric) has a stronger influence on purchase intention for experts than novices, while the volume of reviews has a stronger effect on purchase intention for novices than experts.
(Gretzel & Yoo, 2008)	Travel reviews	Examine how travellers' reviews influence the trip decision making process	1480	Survey	Message	Travel reviews inform accommodation decisions and not so much for en route planning
(Xia & Bechwati, 2008)	Digital camera and Airline ticket	Applying the notion of cognitive personalization to explore the mechanisms underlying the diverse effects of eWOM	85	Experiments	Message, Receiver	Affect intensity, product type (experience vs. search), and message content (experiential vs. factual) all influence the level of cognitive personalization; moreover, valence moderates the effect of cognitive personalization on purchase intention



(C. Park & Lee, 2009)	TOIEC book and Language school program	Analyze how eWOM's effectiveness is influenced by the information valence and the reputation of the website and moderating role of product type.	440	Experiment	Message	Negative eWOM has a higher eWOM impact than positive eWOM, established websites have a higher eWOM effect than unestablished websites, and experience goods have a higher eWOM effect than search products. Both negative eWOM and established websites have a greater impact on experience goods.
(Cooley & Madupu, 2009)	Physicians	Investigate information sources to select physicians for self or loved ones	14	Interviews	Source, Message	Consumers are not anymore dependent on WOM which can be subjective but choose more objective eWOM. More time and effort are spent for searching for loved ones.
(Crutzen et al., 2009)	Intervention about Alcohol	Assess the effectiveness of eWOM on first time visit to an intervention	432	Experiments	Source, Message	eWOM from a friend was more effective than one coming from an institution. Weak arguments were more effective at attracting whilst withholding incentive (peripheral cue)
(Floh et al., 2009)	Books and Hotels	The effect of quality of a product recommendation on buying intentions	339	Experiment	Message	Review quality which are perceived valence and perceived information credibility have significant effect on purchase intention for both search and experience product. No significant difference between positive and negative reviews with moderate valence intensity on purchase intention
(Steffes & Burgee, 2009)	RateMyProfessors.com	The role of social ties in eWOM communication	482	Survey	Source, Interpersonal	eWOM from forums take equal weight as their own experiences. eWOM from forum is more influential than speaking with friends (WOM). Some weak ties are even more influential
(C.-C. Chang & Chin, 2010)	Mini notebook	Investigate the topic of recommendation sources with the inclusion of gender and consumer risk perception variables	396	Experiment	Source, Receiver	Effects of eWOM on purchase intentions were stronger than from advertising or recommender systems. During the decision-making process, females are more inclined to consult advice.
(Benlian et al., 2010)	Digital Cameras	Examine differential effects of recommendations from the provider and consumer on cognitive affective aspects on recommendation usage intentions	527	Survey and Experiment	Source, Interpersonal	Recommendation from a consumer has stronger impact on trusting beliefs and perceived affective quality. Provider recommendations are stronger in affecting perceived usefulness. Trusting beliefs and perceived affective quality are stronger predictors of usage intention than perceived usefulness
(Bronner & de Hoog, 2010)	Vacation	Consumer eWOM in comparison with commercial/marketer generated information	1650	Survey	Source	Both types of information are complementary. Positive and neutral or mixed information are more frequent than negative ones
(L.-Y. Chang et al., 2010)	Body Care products	Relationship between eWOM and purchase decision in the context of body care products	275	Survey	Source, Receiver	Expertise, trustworthiness, search extent, and own experience have positive influence on eWOM effect
(J. Q. Zhang et al., 2010)	Photo-editing program and Anti-virus program	Consumption goals as a moderating role in the relationship between valence and persuasiveness	150	Experiment	Message	When promotion consumption goals (photo-editing program) are involved, positive eWOM is more persuasive. When prevention consumption goals (anti-virus program) are involved, negative eWOM is more persuasive
(Z. Zhang et al., 2010)	Restaurants	Differential influences of consumer based eWOM and professional editors' eWOM on popularity	1242	Content Analysis	Source, Message	Consumer based eWOM of restaurant quality, atmosphere, and service, as well as the volume of eWOM, are favorably linked with restaurant online popularity; however, editor eWOM are negatively associated with customers' inclination to visit a restaurant's homepage.

(Hao et al., 2010)	USB flash drive and Face lotion	Investigate how the type of good moderates the influences of the valence of eWOM	290	Experiment	Message	Positive eWOM has a bigger influence on search products than on experience goods, whilst negative reviews have no discernible effect on these two categories of goods. The impact difference between negative and positive eWOM is greater for experience goods than for search goods.
(Gupta & Harris, 2010)	Laptops	Investigate the impact of eWOM on product consideration and decision-making for an experience product.	198	Experiment	Receiver	eWOM leads to more time spent in considering product. Highly motivated consumers in their information processing are willing to accept the recommendation and switch from their declared attribute preferences. Less motivated consumers tend to make suboptimal decisions
(Nakayama et al., 2010)	PCs, Bestselling Books, Cell Phones, Cars, Vitamins, and Auto Insurance	Effect of the internet on consumer reliance on various purchasing information sources (Self-evaluation, WOM, eWOM, and Expert opinion). The perceived importance of four decision sources was compared with inclusion of 6 products from the SEC framework	549	Survey	Source, Receiver	Despite its ubiquity, the perceived importance of eWOM in decision making is confined to credence goods. Consumers' trust in self-evaluation over WOM for search goods grows as they have access to the internet. However, relying solely on the Internet does not boost self-evaluation confidence for experience and credence goods.
(S.-Y. Shin et al., 2011)	Restaurants	Examine characteristics of eWOM on it eWOM effect and mediating role of source credibility	203	Survey	Source, Message, Interpersonal	Visit intention and source credibility affected eWOM acceptance. Homophily and vividness improved source credibility
(Y. Pan & Zhang, 2011)	music CDs, movie DVDs, and video games, GPS, photo-editing software, and food supplements	Investigate the effects of review characteristics, product type, and receiver characteristics on perceived review helpfulness	400	Content Analysis	Message, Source	Valence and length of eWOM have positive effects on review helpfulness while product type (experiential or utilitarian) moderates this. The relationship between sender innovativeness and review helpfulness are curvilinear
(Racherla & Friske, 2012)	Furniture Stores, Restaurants, and Beauty and Spa	Investigate perceived usefulness in SEC services	3000	Content Analysis	Source, Message	Both sender and message characteristics are correlated with perceived usefulness. Characteristics such as message usefulness, reputation, identity disclosure, and expertise
(Gu et al., 2012)	Digital Cameras	Examine the influence of external and internal eWOM on retailer sales of high-involvement items.	148	Content Analysis	Source, Receiver	Internal eWOM has a minor impact on high-involvement product sales, but external eWOM has a substantial impact.
(K.-T. Lee & Koo, 2012)	Digital Cameras	Investigate attribute and valence of eWOM effect on adoption	319	Experiment	Message, Receiver	Objective eWOM increases message credibility. Negative eWOM have a negative impact on message credibility. Objective information paired with the subjective knowledge of the consumer has a moderating effect
(C. M. K. Cheung et al., 2012)	Beauty Products	Examine the impact of two forms of online social interactions, namely eWOM and observational learning (OL) on purchasing choices.	75	Content Analysis	Message, Receiver	OL information that is based on action is more influential than eWOM that is based on opinion. Furthermore, findings demonstrate that consumer expertise as well involvement have a key moderating effect.

(Jensen et al., 2013)	Digital Cameras	Examine how prospective purchasers evaluate the credibility of anonymous reviewers.	435	Experiment	Source, Message	Two-sidedness leads to greater credibility attribution. High affect intensity led to lower credibility attribution. High reviewer credibility led to high perceived product quality
(Meuter et al., 2013)	Restaurants	investigate the impact of interpersonal WOM and different sources of eWOM	112	Survey	Source	When compared to other eWOM investigated, WOM has a greater impact on behavioral intentions, trust, and attitude towards the company. Independent sources of eWOM, such as Facebook and Yelp.com, have greater clout than company-controlled eWOM
(H. H. Chang & Wu, 2014)	Starbucks	An investigation of the use of negative eWOM	504	Survey	Message, Receiver	Information receivers formed external attributions and perceived information as credible as a result of consensus and vividness; receiver brand commitment moderated the relationship
(Filieri & McLeay, 2014)	Holiday Accommodations	The factors that impact travelers' use of eWOM information in their decision-making	578	Survey	Message, Receiver	Acceptance of information is strongly influenced by product ranking, information accuracy, info value-added, information relevance, and information timeliness. High-involvement travelers process information in both central (information quality) and peripheral (product rating) routes.
(C. H. Lee & Cranage, 2014)	Restaurant	Explain the processing of negative eWOM	241	Experiment	Message	Consensus is critical in determining how potential customers assimilate bad information into their assessments of the company
(Lu et al., 2014)	Cell Phones and Package Tours	Sponsored blogger's recommendation and purchase intention	613	Experiment	Source, Message	Consumers have very positive attitudes about sponsored recommendations when the products mentioned in blog posts are search goods or have high brand recognition, which enhances purchase intention.
(Yeap et al., 2014)	Movies	Determine the most popular eWOM platform for movie reviews, as well as the parameters that make up an effective eWOM platform.	54	Content Analysis	Source, Message	With review sites emerging as the most popular eWOM platform, source credibility was determined to be more essential than information quality.
(Jeong & Koo, 2015)	Smart phones	Investigate the combined impacts of valence and objectivity/subjectivity of eWOM have an influence on consumer judgment, and whether eWOM platforms have a moderating effect on consumer judgment	480	Experiment	Source, Message	Objective negative eWOM evaluations were ranked better in terms of message usefulness. Platforms (marketer or consumer generated) moderated this effect
(Duffy, 2015)	Hotels	Investigate when users are affected by friends (WOM) who have little knowledge of hotels but a good comprehension of the user, and when they are influenced by review sites (eWOM) who have a lot of hotel experience but don't know the user	267	Content Analysis and Survey	Source, Interpersonal	Friends are the most credible source, the greater homophily is valued more. However, circumstances where eWOM is more credible is when certainty is important, so complete information is needed. Most relied on multiple sources, not just one

(Y.-H. Cheng & Ho, 2015)	Restaurants	Social influence on eWOM perceptions	983	Content Analysis	Source, Message	A higher number of followers means a higher level of expertise. Higher image and word count make users perceive it as more useful and practical. Impact of the peripheral route, which are social factors are higher than factors in central route
(Filieri, 2015)	Accommodations and Restaurants	Examine the informational and normative determinants of eWOM diagnosticity, as well as their connections to information adoption.	354	Survey	Message, Source	Consumers are first and foremost affected by the quality of information. Customer ratings and total rankings follows. Volume and Source credibility have limited effect.
(Koo, 2015)	Airline ticketing, Family restaurant, and Skin care services	Examine the interactional effects of valence, tie strength, and service type (SEC) on attitude and purchasing intent.	616	Experiment	Message, Interpersonal	Attitude is influenced by the interactions of valence by tie strength and valence by service types. The interaction between valence, tie strength, and service type affects both attitude and intention, and its impact on intention is mediated by attitude.
(Q. Liu, 2015)	Lady jeans and Parent-child books	Persuasive and awareness effects of eWOM on product sales are investigated.	9014	Content Analysis	Message	Rating has no sig. impact after controlling price. Volume has sig. impact. eWOM effect is larger for experience goods than for search goods. Price has no sig. impact for search goods but has a negative impact for experience goods
(S. Park & Nicolau, 2015)	Restaurants	Explore asymmetric effects of eWOM based on valence	5090	Content Analysis	Message	Consumers perceive extreme ratings which positive or negative as more useful or enjoyable than moderate ratings
(Koo, 2016)	Airline ticketing, Family restaurant, and Skin care services	Tie strength and sender experience in eWOM communications	302	Experiment	Source, Interpersonal	Tie strength and sender experience have positive impact on credibility and intentions. Weak ties can be as persuasive as strong ties when it is from sender with experience
(Y. K. Choi et al., 2017)	Furniture	Message concreteness and temporal distance effects	107	Experiment	Message	If purchase occurs soon, concrete messages are more motivating. Distant future purchases are motivated by abstract messages
(De Angelis et al., 2017)	Financial and Medical services	Persuasion basing on message abstractness	120	Experiments	Message	Abstract messages are more effective for receivers with high prior knowledge
(Kala & Chaubey, 2018)	Fashion accessories, Apparel, and electronic appliances	eWOM effects on brand image	313	Survey	Receiver	eWOM has a significant effect on brand image. Brand image is a moderator between eWOM and purchase intention
(Filieri et al., 2021)	Tourist attractions	The effects of visual and verbal cues of eWOM	460	Survey and Experiments	Source, Message	Intentions and decisions to visit are influenced by popularity heuristics, performance visual heuristics, and user-generated pictures. Surprisingly, the quality of information had no effect

#### 4.2.3 AUTOMATED RECOMMENDATIONS

A recommender system should inspire trust and be transparent on how it works (Swearingen & Sinha, 2001). They should be more of a trusted friend rather than a hierarchical controller who thinks like the consumer in order to give personalized recommendations (Aksoy et al., 2006; Bauernfeind & Zins, 2005; Senecal & Nantel, 2004). There are differential effects between recommender system types. For overall satisfaction, a simple content-based filter is preferred even if consumers are aware of its lower utility; content-based filtering is preferred when the product is considered sensitive in nature (Burbach et al., 2018; Cremonesi et al., 2011). Experts on the other hand, prefer hybrid recommender systems because both implicit and explicit preference elicitation are available as an interaction between consumer and recommender system (Knijnenburg et al., 2011). Content based and collaborative filtering have distinct influences on the behavioral intention and acceptance of the system for users (Y.-Y. Wang et al., 2012). A recommender system who is aware of the context is easier to use and its acceptance is high due to preference learning (Armentano et al., 2014). A recommendation coming from a recommender system works well when it conforms to eWOM. Contradicting recommendations coming from the system and eWOM can be damaging to the retailer (Baum & Spann, 2014). In the realm of CRS, the main point of interest is anthropomorphism. A CRS who is anthropomorphized is perceived as more accurate and leads to information disclosure from the consumer and recommendation adherence (Dietz et al., 2019; Ischen et al., 2019). Anthropomorphism increased social presence which in turn, increased trusting beliefs; it also gives more sense of control proven by the reactance of the consumer (Morana et al., 2020; Pizzi et al., 2021). A CRS should show specialization instead of being a general recommender, in this way, expertise and message trustworthiness can be achieved (Tan & Liew, 2020). Although CRS was perceived as more animate and anthropomorphic, they do not differ in perceived intelligence compared a normal web platform (Laban, 2021). The conversational aspect of the system evoked affective trust which aided benevolent evaluation and recommendation acceptance compared to non-conversational advisors (Hildebrand & Bergner, 2021). To some degree, Whang & Im, (2021) agree that a CRS is seen as a pseudo human detached from the provider which can develop a parasocial relationship with the consumer.

Recommendations coming from a robot or humanized AI are not taken the same way as those coming from humans. These recommendations are often accompanied with explanations for the consumer. Explanations increase acceptance of the recommendation; they are important for functionality and are seen as useful and positively impacts satisfaction and perceived relevance (Cramer et al., 2008; Dominguez et al., 2019; Zanker, 2012). The explanations are there to show why a product or service was recommended to the user. “Why” justifications positively impacted perceived transparency which consequently affects perceived control and trusting beliefs ultimately leading to recommendation adoption; surprisingly, “why not” justifications did not have a significant impact (Wilkinson et al., 2021). The framing of the message has distinctive outcomes. Messages that are framed as user-based, such as “people who like this also like...” get more attention than item-based framing such as “similar to this item” (Gai & Klesse, 2019). Experiential decision makers who receive argumentative explanations perceive higher information quality, information sufficiency and overall satisfaction, these effects were not seen for rational decision makers (Naveed et al., 2018). A rating provided by the recommender system serves as an anchoring effect on the preference of the consumer which can be influenced by perceived reliability (Adomavicius et al., 2013). Incorporating sentiments in recommender systems reinforced information usefulness, decision confidence, product knowledge, and purchase intention; the usage of emojis builds social attractiveness, competence, and credibility as compared to verbal

messages only (Beattie et al., 2020; L. Chen et al., 2019). To accentuate the power of algorithms, precise number presentations are shown to users. When the message contains a precise number on why that recommendation was given, it resulted to higher evaluations due to information accuracy and objective product quality (M. Kim et al., 2021). Paradoxically, an intentionally inaccurate recommendation is trusted more than necessary, as long as these are communicated as personalized to the consumer (Harman et al., 2014).

To gain recommendations from algorithms, users must inform their preferences by giving feedback. Preference elicitation happens both implicitly and explicitly to counter the so called “cold start” problem for AI. A combination of implicit and explicit feedback increases engagement and satisfaction. Perceived usefulness has a higher impact than perceived ease of use which is dependent on the skills of the user (Armentano et al., 2015). Consumers with low product expertise have perceived usefulness as the main factor when using CRS while perceived enjoyment is salient for users with high product expertise (Baizal et al., 2016). The main topic that frequently occurs for users of recommender systems or CRS are privacy concerns. Highly personalized recommendations work when they have processed data which the user has given. Therefore, it is in the interest of providers to build trust between the automated recommender and the consumer, especially in aiding decision making that leads to purchase intention (Bauernfeind & Zins, 2005). The challenge is to justify disclosing information about oneself to the AI for the purpose of providing personalized recommendations (Burbach et al., 2018). First, the attitude to being monitored should be assessed which is the perception of what the intention of the recommender system is; Nowak & Nass (2012) asserted this by questioning to whose benefit does the recommender system use the data for? Is it for the benefit of the provider which is the company or the consumer? Credibility, anthropomorphism, competence, social presence, and informativeness have led to a trusting relationship towards CRS (Yen & Chiang, 2021). Knowing that anthropomorphism plays a crucial role in CRS interaction, embodiment of the system solely does not affect trust; there must be preference elicitation (Herse et al., 2018). To elicit the preference of consumers, interactions should be inspiring and enjoyable (Neidhardt et al., 2015). Rapport building dialogue increased the intention to follow the recommendation and an improved perception of the system; dynamic feedback adds to perceived accuracy and trust regardless of actual accuracy of the recommendation; dynamic response delays of a CRS increased perceived humanness and social presence (Gnewuch et al., 2018; Pecune et al., 2020; Schaffer et al., 2015). Attempts have also been made to cater to consumers with algorithm aversion albeit with minimal effects. Justifying disclosure messages does not necessarily increase disclosure although arranging the order of disclosure requests lead to short term success (Knijnenburg & Kobsa, 2013). Depending on who initiated the conversation, perceptions of risk occur, a system-initiated conversation is riskier than a user initiated one, both options do not differ in perceived anthropomorphism (Laban & Araujo, 2020b). Perceived personalization aids in boosting trusting beliefs and intention (Whang & Im, 2018). A disadvantage of receiving recommendations from AI is its influence on consumer preferences. AI recommendations strengthen consumer preferences which are related to so called information cocoons; it has been found that information cocoons decline the decision quality of the consumer (S. Chen et al., 2021). The filtering aspect that is supposed to lower the cost of searching can therefore be a trap for consumers in these information cocoons, hindering them from discovering a variety of products.

Author and Year	Content Recommended (Products and Services)	Study Aim	Sample	Method/s	Codes for Analysis	Findings
(Swearingen & Sinha, 2001)	Books and Movies	Investigate what design elements of RS make item more convincing	19	Experiment	Source, Message, Interpersonal	Effective RS inspires trust and is somehow transparent. Recommends new not yet experienced products with pictures and community rating,
(Senecal & Nantel, 2004)	Computer mice, Calculators, and Red Wine	Examine the influence of online recommendation sources on online product choices	487	Experiment	Source, Receiver	Source labelled "recommender system" was more influential than traditional sources such as "human experts" and "other consumers" due to personalization possibilities
(Bauernfeind & Zins, 2005)	Airlines, Accommodation, and Digital Cameras	Explain what factors affect satisfaction towards RS	150	Experiment	Source, Interpersonal	Trust plays an important role in supporting decision making and purchase intention. RS should focus to be a trusted friend instead of hierarchical controller
(Aksoy et al., 2006)	Cell phones	Investigate the role of similarity between recommendation agent and user	79	Experiments	Source, Receiver	It helps the user when a recommendation agent thinks like them in terms of attribute weights and decision strategies
(Gretzel & Fesenmaier, 2006)	Beach vacations	Investigate perceived fit of recommendation of RS and perception of preference elicitation	702	Experiment	Message, Receiver	Relevance, transparency, duration, and effort required are important value cues which impacts perceived enjoyment and fit of recommendation
(K. Yoo & Gretzel, 2006)	Travel	The role of credibility in RS	401	Survey	Source	Perceived trustworthiness and perceived expertise as credibility constructs have an impact on RS perception
(Pu & Chen, 2007)	PC and Camera	Examine the interface which inspires trust	72	Experiment	Message, Interpersonal	Products grouped according to tradeoffs build trust. Presence of negative valence in form of trade off
(Hyan Yoo & Gretzel, 2008)	Travel	The impact of perceived credibility on people's preferences for RSs as sources	109	Survey	Source, Receiver	Two dimensions of credibility have been confirmed, trustworthiness and expertise. Gender of user differences are found. Users prefer humans over RS as sources due to lack of credibility and gender-specific preferences
(Cramer et al., 2008)	Artworks	Role of transparency in trust and acceptance of content-based RS	60	Experiment	Message, Source, Interpersonal	Explanations increased acceptance. Transparency does not improve trust. Certainty shown by RS does not impact trust and acceptance
(J. Choi et al., 2009)	TOEIC books and Ringtones	The impact of social presence on RS evaluation	248	Experiment	Interpersonal, Message	Social presence increases reuse intention and trust. Reuse intention effect from social presence is less for utilitarian products than hedonic products
(K.-H. Yoo & Gretzel, 2009)	Travel	Anthropomorphism cues effects on RS evaluation	137	Experiment	Source	Virtual representative's credibility increased perceived credibility, liking, and perceived attractiveness
(Ochi et al., 2010)	Fragrances and Rugs	Investigate user responses on product type RS recommendation approach	80	Experiment	Source, Message, Interpersonal	No main differential effects between content and collaborative approach in search and experience products. Although two-way interactions were found suggesting design implications

(Cremonesi et al., 2011)	Movies	Investigate the quality of different RSs from the perspective of a user	210	Experiment	Source, Receiver	Simple non-personalized algorithm is perceived well for overall satisfaction, but users are aware of low utility. Perceived novelty is higher for content based than collaborative filtering. Statistical accuracy metrics is not a good measure for perceived quality by users
(Knijnenburg et al., 2011)	Energy saving	Examine different interactive methods in RS	158	Experiment	Source, Receiver	Most users, especially domain experts, are most satisfied with hybrid RS which has implicit and explicit preference elicitation. Novices are satisfied with non-personalized RS which displays just most popular items
(Cremonesi et al., 2012)	Movies	Examine by a quality perspective, the persuasion potential of RS	210	Experiment	Source, Receiver	Algorithmic attributes are not a good measure for perceived quality for users. User experience is more likely to inspire perceived quality. RS tend to diversify purchases towards less obvious choices (long-tail). Perceived novelty likely more influential than perceived accuracy
(Y.-Y. Wang et al., 2012)	MP3 Players and Printers	Explore factors in acceptance of two types of RS and products	204	Experiment	Source, Message	RS type (content and collab) and product type (hed and util) have differential effects on behavioral intention and acceptance
(Hennig-Thurau et al., 2012)	Movies	Influence of Group RS on decision making	214	Experiments	Source, Interpersonal	Automated group recommenders offer more valuable information but depends on social relationship.
(Nowak & Nass, 2012)	Movies	Impact of behavioral monitoring and perceived system benefit in RS	52	Experiment	Source, Receiver	Attitude to being monitored depends on the perception of system intentions, benefit to consumer or company
(Zanker, 2012)	Spas	Examine the influence of knowledgeable explanations on perception of RS	134	Experiment	Message	Explanations are important for functionality which increases perceived utility and intention to use
(Adomavicius et al., 2013)	TV programs	Investigate whether RSs manipulate consumer preferences	458	Experiments	Message	Rating by RS has an anchoring effect on consumer constructed preference. Effect is influenced by perceived reliability
(Said et al., 2013)	Movies	User evaluation of dissimilar recommendation	132	Experiment	Message	No significant difference for perceived usefulness for diverse recommendations (dissimilar, furthest neighbor)
(Knijnenburg & Kobsa, 2013)	Apps	The role of privacy and information disclosure in context aware RS	493	Experiment	Message, Interpersonal	Justifying disclosure messages does not increase disclosure. They are perceived as valuable, but it decreases trust and satisfaction. Order of disclosure request increases disclosure but only in short term
(Armentano et al., 2014)	Movies	Examine impact of preference elicitation and acceptance of RS	118	Experiment	Source	Context aware RS is easier to use, and acceptance is high due to preference learning
(Baum & Spann, 2014)	Cameras, Hotels, Clock radios, Coffee	Analyze the interplay between eWOM and RS effect on consumer decision making	1332	Experiment	Source, Message	Inconsistent eWOM negatively influences purchase decisions. Positive eWOM in addition to RS recommendation increases effectiveness of RS. If eWOM contradicts RS recommendation, positive eWOM may even have negative consequences for online retailers
(Ekstrand et al., 2014)	Movies	Examine the different perceptions of recommender algorithms	582	Experiment	Message	Satisfaction is positively dependent on diversity and negatively dependent on novelty. Satisfaction predicts final selection



(Gedikli et al., 2014)	Movies	Compare different explanation types of RS	125	Experiment and Interview	Message, Receiver	Content based tag cloud are effective for perceived transparency and satisfaction but uses higher cognitive effort
(Harman et al., 2014)	Night Venues	Analyse trust dynamics in RS	400	Experiments	Message, Receiver	Inaccurate recommendations are trusted more than necessary. Personalized inaccurate recommendations are trusted much less than non-personalized inaccurate recommendations
(Armentano et al., 2015)	Movies	Examine user skills in RS acceptance	116	Experiment	Receiver	Perceived usefulness has a higher impact than perceived ease of use. Users skills impact perceived ease of use which directly influences perceived usefulness
(Neidhardt et al., 2015)	Travel	Explore picture-based approach as implicit preference elicitation	997	Survey	Message, Interpersonal	Interactions were perceived as inspiring and enjoyable
(Schaffer et al., 2015)	Movies	Impact of dynamic feedback in RS interactions	129	Experiment	Message, Interpersonal	Dynamic feedback by removing or adding items adds to perceived accuracy and trust on RS regardless of actual accuracy of recommendation
(Y.-Y. Wang et al., 2015)	Phones, Laptops, PCs, Cameras, Printers, MP3 Players, and GPSs	Investigate RS and product type on behavioral intention	80	Experiment	Source, Message	RS type (content and collab) moderates the relationships which determine behavioral intention. Product type (hed. and util) does not have a moderating effect.
(Baizal et al., 2016)	Smartphones	Examine factors that influence adoption of CRS	35	Experiment	Receiver	Perceived usefulness is the main factor for users with low product expertise. Perceived enjoyment plays a role for users with high product expertise
(Y. K. Choi et al., 2017)	Apps	Investigate the impact of personalized RS in a self and social interaction perspective	156	Experiment	Interpersonal, Receiver	Social presence and self-referencing significantly increase perceived accuracy and novelty which in turn increases satisfaction and purchase intention
(Adomavicius et al., 2018)	Songs	Analyze RS effects on willingness to pay	169	Experiments	Message	Recommendations generated randomly or are not based on preferences impacts willingness to pay
(Burbach et al., 2018)	Books, Phones, and Contraceptives	Investigate product category influences on privacy perceptions of RSs	197	Survey	Source, Message, Interpersonal	Products that are more sensitive increased preference for content-based filtering without storing personal data. Trust based and social approaches RS which uses data from social media were mostly rejected
(Gnewuch et al., 2018)	Mobile phone plan	Dynamic response effect in CRS interaction	79	Experiment	Message, Interpersonal	Dynamic response delays increased perceived humanness and social presence which lead to greater satisfaction
(Jin et al., 2018)	Music	Influence of personal characteristics and controllability on RS perception	240	Experiment	Receiver, Interpersonal	Controlling profile and algorithm parameters are most favorable. Users with expertise perceived recommendations to be of high quality which increased acceptance
(Naveed et al., 2018)	DSLR Cameras	The role of argumentative explanations in RS	60	Experiment	Message, Receiver	Experiential decision makers who receive argumentative explanations perceive higher information quality, information sufficiency and overall satisfaction. These effects were not seen for rational decision makers
(Whang & Im, 2018)	Fragrance oils	Investigate sponsored recommendations and RS type on trusting beliefs and intentions	273	Experiment	Message, Receiver, Interpersonal	Perceived personalization increased trusting beliefs and intentions. Disclosing sponsored recommendation increased trusting intention only for low involvement
(Herse et al., 2018)	Restaurants	Factors that influence trust in CRS	96	Experiment	Source, Interpersonal	Embodiment solely does not seem to affect trust. Only when preference elicitation is added, trust is increased in CRS

(Zhao et al., 2018)	Movies	Analyze different ML based RS and user feedback	1508	Experiment	Interpersonal, Receiver	A combination of implicit and explicit feedback increases engagement and satisfaction. At the right balance to mitigate user effort
(L. Chen et al., 2019)	Digital Cameras and Laptops	Investigate the perception of integrating sentiments in RS	229	Experiments	Message, Receiver	Integrating sentiments in a critique-based RS increases product knowledge, preference certainty, decision confidence, perceived info usefulness, and purchase intention
(Dietz et al., 2019)	Travel	CRS acceptance in Travel related recommendation	104	Experiment	Source	CRS has higher perceived accuracy but at the cost of ease of use
(Dominguez et al., 2019)	Artworks	The influence of explanations and accuracy on visual RS	121	Experiment	Message	Explanations of recommendations are useful and increases satisfaction and perceived relevance and explainability
(Pecune et al., 2019)	Movies	Social explanation effect in Movie CRS	60	Experiment	Message	Social explanations increased perceived quality regardless of intrinsic quality of recommendation
(Ischen et al., 2019)	Health Insurances	Privacy dynamics in CRS recommendations	231	Experiment	Source, Interpersonal	Perceived anthropomorphism led to higher information disclosure and recommendation adherence. Results do not hold when compared to website, a website was perceived as equally high in anthropomorphism
(Gai & Klesse, 2019)	Books	Message framing effects on click-through rates	1129	Experiments	Message	User-based framing increases click-through rates more in comparison to item-based framing
(Matt et al., 2019)	Music	Investigate RS, Sales, and user diversity interactions	637	Experiment	Receiver	Perceived diversity by user does not reflect actual diversity measures
(Millecamp et al., 2019)	Music	User characteristics and explanation effects	71	Experiment and Interview	Receiver, Message	Users with low need for cognition benefited from explanations. Users with higher need for cognition may get a reduced confidence when presented with explanations
(Kunkel et al., 2019)	Movies	Effect of personal and impersonal explanations on trust in RS	93	Experiment	Source, Message, Interpersonal	Explanations by users were perceived as higher quality than the system's explanations. Explanation quality impacts perceived recommendation quality and trust. RS should provide richer explanations
(Beattie et al., 2020)	Restaurants	Usage of emoji effects in CRS communication	96	Experiment	Source, Message	For both human and CRS communication, usage of emojis increased social attractiveness, competence, and credibility compared to only verbal messages
(Ischen et al., 2020)	Health insurances	Factors to improve persuasion of CRS	242	Experiment	Source, Interpersonal	Enjoyment was a key factor in improving recommendation adherence and attitudes for CRS in comparison to website. Perceived anthropomorphism was not relevant
(Laban & Araujo, 2020a)	Restaurants	Investigate personalized anthropomorphic CRS recommendations	266	Experiment	Message	Customized in comparison to personalized would exhibit less resistance and more adherence to recommendations
(Laban & Araujo, 2020b)	Restaurants	Investigate initiation technique in personalized recommendations in CRS	141	Experiment	Source, Interpersonal	System initiated in comparison to user initiated is perceived as less in control and therefore riskier. User and system-initiated recommendations do not differ in perceived anthropomorphism
(Longoni & Cian, 2020)	Hair treatment, House properties, Chocolate cake, Winter coats, Chocolate varieties, Real estate service, and Recipes	Provide robust evidence of a word of machine effect by explaining utilitarian and hedonic tradeoffs in choosing between AI or human recommendations	2565	Experiments	Source, Message, Receiver	Preference for AI recommendations when utilitarian attributes are salient. Effect is eliminated for augmented intelligence in which AI and human both aid decision making. When user tries to match their unique preferences, they choose human over AI in both hedonic and utilitarian goals. Preference for AI for utilitarian goal only is attenuated when intervention protocol is presented, making AI recommendations more attractive for hedonic goals
(Pecune et al., 2020)	Recipes	Socially aware CRS effects of personalized recommendations	106	Experiment	Interpersonal	Rapport building dialogue increased intention to follow recommendations and improves perception of the system

(Jin et al., 2020)	Music	User characteristics and control effects in Music RS	90	Experiment	Receiver	Users who have music sophistication accepted recommendations with more own control. Perceived diversity also increased
(Morana et al., 2020)	Financial Investment	Impact of anthropomorphism on investment decisions	183	Experiment	Source, Interpersonal	Anthropomorphism increased social presence which consequently increased trusting beliefs. Trusting beliefs increased likeliness to follow recommendation. Social presence does not have a direct effect on likeliness to follow recommendation but indirectly through trust
(D. Shin, 2020a)	News	Investigate interaction between user, RS, and performance	328	Experiment	Interpersonal	Heuristic affect (subjective feelings about transparency and accuracy) happens during interaction. Building trust towards the algorithm could enhance performance of RS
(D. Shin, 2020b)	Movies, Books, and News	Investigate where trust is linked in personalized recommendations	371	Experiment	Source, Message	Fairness, accountability, transparency, and explainability lead to perception of trustworthiness and usefulness. AI thus have heuristic roles in decision making
(Burbach et al., 2020)	Health-related context	Examine the importance of privacy perceptions according to data provision to RS	163	Experiment	Message	Users disclose only general data and only provide health-related data when context becomes health critical
(Tan & Liew, 2020)	Beauty, Health, Camera, and Laundry	Specialist and generalist CRS effects	122	Experiment	Source, Interpersonal	Specialist CRS increased perceived expertise, message trustworthiness, social presence, trust, and purchase intention
(Srivastava et al., 2020)	Books, Movies, and Music	Investigate gray sheep behavior in RS	3668	Experiments	Receiver	Removing gray sheep users (eccentric tastes) increases collaborative filtering performance
(J. V. Chen et al., 2021)	Cameras, Books, Fashion clothing, Sports clothing, Smartphones, Hotels, DVDs, and Food and Beverages	Decisional guidance and communication style effects of CRS in information seeking	249	Experiment	Message, Interpersonal	Higher cognitive fit for suggestive guidance in comparison to informational guidance. Higher for social oriented communication style in comparison to task oriented. These results are especially strong for search task instead for just browsing task
(Ghori et al., 2021)	Amazon, YouTube, Netflix, and Spotify contents	Explore users' behavior towards RS	40	Interviews	Receiver, Interpersonal	Basing on the understanding, attitude, and intentions of users, they change their interaction to gain desired RS behavior
(Ahn et al., 2021)	Air purifier	Analyze the role of perceived similarity and psychological distance on persuasion	120	Experiments	Source, Message, Interpersonal	Users feel more psychologically distant with AI recommender than with human due to different levels of similarity. Psychological distance decides whether desirability or feasibility messages are more effective. Increased perceived similarity is achieved by anthropomorphism and makes secondary features message more effective
(J. Kim et al., 2021)	Music and Books	Analyze the impact of number presentation on trust and acceptance of AI recommendations	312	Experiments	Message, Interpersonal	Precise number presentation led to high trust which impacted higher evaluations and behavioral intentions. Preciseness effect is moderated by information accuracy and objective product quality
(M. Lee et al., 2021)	Cryptocurrency	Investigate CRS in the social-technical gap of trust	61	Interviews and Observations	Source, Message	CRS has a potential dual role as object of trust and mediator of trust towards cryptocurrency
(Liew et al., 2021)	Electronics, Sportswear, Fashion and accessories, and Body care	Impact of expertise cues of CRS	71	Experiment	Source, Interpersonal	CRS with expertise cues increased perceived source expertise, platform trust, and trust integrity which led to purchase intention

(Laban, 2021)	Restaurants	Animacy and intelligence roles of CRS and web platform	160	Experiment	Source	CRS was perceived as more animate and anthropomorphic. There is no difference of intelligence perceptions between CRS and web platform
(J. Kim et al., 2021)	Fashion	Self-disclosure and anthropomorphism of CRS effects on decision making	234	Experiment	Source	Self-disclosure with facial expression increased intention to use
(Mozafari et al., 2021)	Liability insurance	Ways to mitigate negative effects of CRS self-disclosure	257	Experiment	Source, Message	CRS disclosing identity does reduce trust, but it is mitigated by selectively presenting expertise or weakness information
(Pizzi et al., 2021)	Mobile service providers and Car rentals	Control effects in anthropomorphized and non-anthropomorphised CRS	400	Experiments	Source, Receiver	Non-anthropomorphised increased reactance (less control) but lead to higher satisfaction. Reactance is linked with Choice difficulty, certainty, and satisfaction
(Roy & Naidoo, 2021)	Hotel, Smartphone, and Business suit	Analyze the role of anthropomorphic conversation styles and time orientation	523	Experiments	Receiver, Interpersonal	Present oriented users prefer warm rather than competent. Future oriented users prefer competent rather than warm conversation style
(S. Chen et al., 2021)	Keyboards and Car Tyres	Investigate the downside of AI recommendation on decision quality	105	Experiments	Message, Receiver	AI recommendations strengthens users' preferences which are related to information cocoons. Information cocoons decline decision quality
(Chinchanachokchai et al., 2021)	Beer	Investigate the moderating effect of user expertise in the evaluation of RS types	136	Experiment	Source, Receiver	Expert users prefer user based collaborative filtering to content-based filtering. No differences were found for novices
(Hildebrand & Bergner, 2021)	Financial Investment	Investigate CRS in financial decision making as surrogates of trust	875	Experiments	Source, Interpersonal	Conversational advisors evoked more affective trust compared to non-conversational advisors. Increase in benevolent evaluation and recommendation acceptance
(D. Lee & Hosanagar, 2021)	30 Product categories	Analyze the moderating role of product attributes and reviews in RS purchasing stages	184,375	Experiment	Source, Message	Awareness impact is higher for utilitarian and experience products in comparison to hedonic and search product. Saliency impact is higher for hedonic products than utilitarian products. RS recommendations serve as complement to review ratings
(Liang et al., 2021)	Movies and COVID-19 sessions	CRS self-disclosure impacts on trust and recommendation effectiveness	372	Experiment	Interpersonal	CRS self-disclosure was reciprocated by user self-disclosure which led to recommendation agreement
(Whang & Im, 2021)	Herbal tea, Tea infuser, Beach mat, Sunscreen, and Beach towel	Effect of human likeness and parasocial relationship in website versus CRS perception of recommendations	502	Experiments	Source, Message	CRS are perceived as pseudo human agents detached from the provider while websites are perceived as a tool interface which increased positive perception and evaluation of websites. No difference is seen for search and experience product
(Wieland et al., 2021)	News	Explore satisfaction with text-based RS	588	Survey	Message	Users prefer recommendations which are similar but also novel but not necessarily unexpected. Serendipity, the right balance between similarity and novelty
(Wien & Peluso, 2021)	Laptops, Headphones, and Smartphones	Examine product type and cognitive processes in AI and human recommenders	610	Experiments	Source, Receiver	Human recommenders are more effective for hedonic products than AI recommenders due to stronger mentalizing and self-referencing. Humanizing AI increases mentalizing and self-referencing responses

(Wilkinson et al., 2021)	Movies	Justification style effect on CRS recommendations	310	Experiment	Message, Interpersonal	"Why" justifications increase perceived transparency which impacts perceived control, trusting beliefs and ultimately recommendation adoption. "Why not" justifications have no significant impact
(Yen & Chiang, 2021)	Clothing, Accessories, Travel, Shoes, and Foods	Analyze trust factors and purchase intention in CRS	30	Survey and Experiment	Interpersonal	Credibility, anthropomorphism, competence, social presence, and informativeness lead to trust which in turn impacts purchase intention
(Yoon & Lee, 2021)	Sneakers	Investigate perceived empathy and need for cognition effects in AI recommendations	200	Experiment	Source, Receiver	AI in comparison to human expert increased technology quality and personalization quality. High cognitive need increased empathy by personalization quality. Low cognitive need increased empathy by technology quality
(Ahn et al., 2022)	Mouse and Scented candle	Influence of gender stereotypes on AI recommendations	300	Experiments	Source, Message, Interpersonal	Male AI recommenders were given higher competence. Female AI recommender as higher perceived warmth. Interactive effects of AI gender and product type were found wherein more positive attitude were seen for male AI recommender for utilitarian while female AI recommender for hedonic
(Cai et al., 2022)	Music	User characteristics factors for trust in CRS	148	Experiment	Source, Receiver, Interpersonal	Trust propensity and domain knowledge positively impacted trust. Users with high conscientiousness trusted mixed initiative system
(Rix et al., 2022)	Articles	Investigate context dependent purchase intention of AI generated content	298	Experiment	Source, Message	Algorithm appreciation was found in AI authorship which increased purchase intention. Consumption context (hedonic and Utilitarian) was less relevant in AI created content
(D. Shin, 2022)	News	Investigate credibility of AI sources	200	Experiment	Receiver, Interpersonal	Algorithmic literacy and trust are vital in the perception of credibility of the recommendation
(Tan & Liew, 2022)	Electronics, Health products, and home appliances	Single or Multi CRS effects on source credibility, social presence, trust, and purchase intention	154	Experiment	Source, Message, Interpersonal	Single CRS led to higher social presence and trusting beliefs. Multi CRS as product specific advisers did not lead to its supposed effect without labels to accentuate expertise. Multi CRS may have resulted in confusion and unfamiliarity cues which reduced trust

## 5 Future Research Directions

Findings from the systematic review have implications and possible future directions for researchers. There is a synergistic effect between eWOM cues and recommender systems. It is thus necessary to study in what contexts do recommender systems complement eWOM cues. As Lee & Hosanagar (2021) mentioned, recommendations from the system complement review ratings. Hybrid recommender systems used by enterprises today are sophisticated in providing content that will catch the attention of consumers but can consequently be thwarted by negative eWOM. Recommendations from eWOM which contradict the recommendation of the system can backfire on the retailer regardless of the valence of eWOM (Baum & Spann, 2014).

Studies on recommender systems and CRS have focused on consumer's acceptance of these systems. A shift of focus from the source to the message is an avenue for future research by examining how consumers evaluate different messages coming from the same AI. Other avenue of investigation is on how to strengthen trust towards AI by implementing augmented intelligence. A CRS can be persuasive in hedonic contexts with the help of a human expert as researched by Longoni & Cian (2020).

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