Trust Issues Automatic Recommendation Systems

Master Thesis

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1. Abstract

The emergence and eventual proliferation of the internet over the past three decades has had noteworthy impacts on e-commerce. While this is the case, the presence of large amounts of information have led customers into making irrational purchase options; prompting companies to develop varied automated online product recommendation systems to aid buyers in reducing information overload. Although such systems have proven effective to a certain extent, customers have raised concerns towards providers' business interesting and their own privacy concerns. Following this controversy, the paper seeks to identify models of enhancing users' willingness to accept recommendations from automated systems.

The paper proposes that online businesses are taking into account influencer marketing, utilizes the special features that the influencers have. The paper proposes a user recommendation system that prototypes the preference for users and the involved items concurrently. In the realm of the paper, curators ought to enrich it with additional personal insights. The human aspect of the curated system enhances user trust as well as transparency; emotional trust influences purchase options. The paper also hypothesizes that the customers who utilize the curator system would have a higher acceptance rate of its recommendations than the typical recommendation system. Following this, the paper assumes that trust mediates between the willingness to accept the recommendation and the types of system utilized. Lastly, it proposes that higher transparency of the recommendation process systems bolsters the relationship between perception of trust and the willingness to accept recommendations.

The findings of this paper are resounding. The general automatic recommendation includes curators, the consumers' readiness to accept the recommendation increases. In the realm of the second assumption, while trust influences the customers' decision to repurchase and to renew subscriptions, there is a full mediation effect between RSs adoption and the users' desire to accept. In the third assumption, both the expertise and popularity of the curator have a positive impact on the willingness to accept recommendations. The fourth hypothesis was unexpectedly rejected. Most of literatures have proved the otherwise, but some literatures confirmed with the result that the direction of the impact on trust might be depends on circumstances. Moreover, while the online nature of the research and time constraints limited the research, the research provides insights to managers, particularly in comprehending the effective use of curators to increase users' trust in the automatic recommendation systems.

2. Introduction

Following the stream of digitalization, and the rapid growth of e-commerce, consumer purchase decisions are increasingly made online. The large-scale adoption of the internet in daily life is the biggest event that has affected marketing over the past three decades. In the context of this internet era, information load, massive and varied options are provided to society. Having a large number of options might sometimes negatively affects customers buying intentions (Graeme, 2009), and the ensuing information overload and pressure on information processing can lead buyers to make irrational and simplified choices (Carmon et al., 2003). This not only affects customer satisfaction, but also hinders many opportunities for organizations to grow, especially under the e-commerce environment which brought larger perceived risk to customers (Pedro et al., 2014). It has formed a customer need of having a tool that could help them to make fast, convenient, and accurate decisions.

This phenomenon has offered a fundamental basis for the emergence of a automated online product recommendation systems, to help buyers and individual users reduce information overload by reflecting their specific needs, preferences, prior purchase histories, or demographic profiles (Izak & Weiquan, 2005). Moreover, numerous opportunities abound for businesses to better attach and serve customers with both the progress and prevalence of Webbased technologies (Izak & Weiquan, 2005).

Existing literature has already revealed that automatic recommendation systems are the most influential recommendation source on consumers' online product choices (Bo & Izak, 2007), as it decreases customer's search costs and effort especially on the online retailer platforms as it is an independent third-party website that provides more objective information. (Sylvain & Jacques, 2004) However, since the connection between the recommendation systems and their users is an agency relationship, users are uncertain about whether RAs are working for them specially or serving the other parties who have make them available, including merchants and manufacturers (Bo & Izak, 2007). The most pronounced issue involved in recommender adoption is the consumer's trust in them. At the current condition, as recommendation systems develop and gradually become widely known, people start concerning more about their privacy and the intention behind the recommendations promoted by platforms, which causes dissatisfaction and decreases the credibility and user's willingness of accepting recommendation systems.

Trustworthiness or credibility is a basic element that ensures the happening of trades between buyers and sellers, particularly in the rapidly evolving online environment. Due to consumers' increased technical and commercial sensitivity, dispel the doubts of customers accepting recommendations gradually becomes one of the main task organizations should focus on. For instance, customers would doubt the online system due to the distance between suppliers and users, which emphasized by the absence of direct attachment of their recommendation service and one of the biggest concern of users is that it can be easier for the E-vendor to take advantage of online users (Izak & Weiquan, 2005).

In order to fulfill the empirical gap, the question this paper will mainly analyze is:

"How to enhance users' willingness of accepting recommendations from automatic recommendation systems?"

Nowadays, with the rising and expansion of social media, there is a new concept called influencer marketing that has been described as the "next golden goose" of marketing (Newman, 2015). Organizations use or cultivate influencers who as third-party endorsers attract audiences and shapes their attitudes by posting pictures, videos, articles through social media (Karen et al., 2010). Sylvain and Jacques found that the recommendation source "other customers" was perceived as more trustworthy than recommendation systems (Sylvain & Jacques, 2004) but less professional than human experts. This research would like to take these two findings into consideration to develop a general recommendation system. The improved system will be named as Curator System in this paper according to the definition of the curator, which is another form of influencers, usually have a certain level of expertise or influence as an opinion leader(Jianling, Ziwei & James, 2020). Therefore, in this paper, two main types of the curator will be investigated, one is the curator who focuses on using their expertise, another one is influencer curator who focuses on using their fame and influence.

Despite some existing studies having investigated the importance of trust for RSs, effects, and efficiency of social media influencers on market, this paper instead combined influencer marketing as a strategy to see whether involving influencers into the recommendation system will have a positive impact on the trustworthiness of automatic recommendations, thereby enhancing customers' willingness to look into the recommendations and take the recommendations into their consideration set.

3. Literature Review

3.1 Trust lacking in an online environment

Since the evolution of e-commerce, purchasing behavior, information acquisition, and transaction interactions of people have been changed in terms of web applications. The notable examples of this emerging trend are weblogs, Friend-of-a-Friend files, wikis, and social interactions sites. Research has found trust as an important factor that influences consumer behavior (Kharel, 2018). Most consumers perceive online shopping more risky than traditional shopping due to a lack of physical interaction and physical clues(Gustavsson & Johansson, 2006). They are not able to physically view or touch a product before making any purchase, which emphasizes the distance between buyers and products, and the distance between the expected and actual received product (Tatiana et al., 2020). Due to the lack of physical interaction, anonymity, and distance, the potential risk in e-commerce is higher. The majority of the consumers appreciate the real-life experience of touching and trying items. Therefore, it is critical to study online trust to understand why consumers do or do not involve in e-commerce activities(Bach, da Silva, Souza, Kudlawicz-Franco, & da Veiga, 2020).

Furthermore, the monitoring of E-vendor behavior is difficult (Hamelink, 2001), as it gives vendors a higher ability to be opportunistic and take advantage of online consumers (Gefen et al., 2003), resulting in higher consumer perceived risk towards brand and difficulty to build credibility and trust of the brand. The vast information asymmetries in online information bring consumers uncertainty towards vendors' intentions. It is hard for consumers to determine whether the vendor would acting in their best interest (Elizabeth et al.,2015). At the same time, a large number of competitors spawned by network capabilities and environment make it easy for customers to switch online vendors without high switching cost (Hee-Woong et al., 2013). Up to now, substantial studies have been aimed at finding ways to increase customer trust and solve the trust crisis, and also figured out there are still many limitations exist. From another aspect, it also proves the importance and eternal existence of trust issues.

3.2 Automatic Recommendation System

A recommendation system is a system of information filtering that studies user interests based on information from user's profiles or previous behavioral records, and forecast the user's preference or ratings for a given item as well as make a recommendations accordingly (John.O & John.D, 2004; Venkatesh et al., 2002). It alters the way businesses connect with users and strengthens the relations with users, is able to provide a personalized service, and helps buyers and sellers reduce the information overload they face (Bo & Izak, 2007). From the perspective of E-commerce, recommender system help users to search for the products of their preference and interest through the record of knowledge (Isinkaye, Folajimi, & Ojokoh, 2015). Usually, the optimal decision requires an in-depth evaluation of all available alternatives with complete information and substantial knowledge, but it’s nearly inaccessible to humans due to their limited memory and bounded rationality. Kabiawu, van Belle, and Adeyeye (2016) suggested that a reliable information source such as Information and Communication Technologies (ICTs) is an effective solution to improve the bounded rationality situation.

The user-recommender interaction is a mutual action between the recommended system and users. After login to the system, users get multiple recommended items helping the users to select a preferred item (Jingjing & Shawn, 2018). In general, there are two main types of recommendation strategies; content-based recommendation and collaborative filtering. The content-based recommendation normally relies on information such as actors, gender, producer, or director, etc., while collaborative filtering relies on the users’ profile to capture the users’ past rating histories (O'Donovan & Smyth, 2005). Several studies suggest that collaborative filtering is a possible solution like a trust model to improve predictive accuracy in recommendation because recommendations are based on the rating history from a suitable recommendation set(Bach et al., 2020; O'Donovan & Smyth, 2005).

Using a recommendation system is expected to improve the quality of consumers’ decision making. These systems use recommendation agents (RAs), software agents that provoke the consumers’ interest for products either implicitly or explicitly. However, research suggested that different types and characteristics of RAs exert differential influence on consumers’ decision efforts, decision quality, and trust (Xiao & Benbasat, 2007). Moreover, the providers’ capability plays a key role in building users’ trust in RA. For example, Xiao and Benbasat (2007) suggested that there are several other factors that moderate the effects of RA on consumers’ decision-making process. For example, they found that the effects of RA use and characteristics of RA on product choice, decision efforts, and decision quality are stronger for the multifaceted products. That means that if consumers have higher product expertise, their decision quality will be less likely affected by RAs. Alternatively, in the case of consumers' higher risk perception of the product, the decision-making process is highly affected by the RA. This suggests that users' evaluation of RA is dependent on many factors including, RA use, RA characteristics (such as input, design, output), and some other factors related to the user, product, and user-RA interaction.

In addition to the above, several studies have found that another key factor affecting the consumers' trust in online environment is privacy (Yuanchun et al., 2010). Recommendation systems rely on the user's profile to give recommendations as they work on the concept that users tend to purchase those products that they have purchased already. You Tube is a as a real life example, it usually offers the users only those videos that are similar or related to what they have already watched on their recommendation page. This is because that recommendation systems track users' data and browsing history. These privacy issues increase the customers' perceived risk and lower the trust in using recommendation system (Yuanchun et al., 2010).

The study of trust issues in the recommendation system is not a new topic. Many scholars have researched the topic from different perspectives to examine what can affect the users' decisionmaking process based on a recommendation system (Xiao & Benbasat, 2007). However, the evolution in the e-commerce industry and upgrades of RS has added new features which have made it easier to use RS with more complicated back end operation and turned out to be standard on various platforms such as image social platforms, video platforms, and short video channels, like Tiktok, and the Facebook. A recent update in this regard is the feature of Social Media

Shopping that refers to companies' direct selling points within the platforms by using content. It forms a great combination with RS on the basis of marketing (Sidharth Muralid &Lin, 2015). According to (y Monsuwé, Dellaert, & De Ruyter, 2004) consumers perceive human expertise and interaction more trustworthy in online shopping and it acts as a factor that increases trust in e-commerce.

Although the RS upgrades in terms of new features and types has offered many opportunities to the e-commerce retailers, it also brings new risks. Researchers are focusing to explore those risky areas. For example, Sylvain and Jacques have critically examined the comparison between the RS and other different information systems. They found that users perceive the recommendations of other consumers as more trustworthy than the recommendation received from RS (Sylvain & Jacques, 2004). The findings of this research provide part of the basis for inferring the hypothesis of this paper.

3.3 Influencer Marketing and curator system

3.3.1 Influencer Marketing

With the rapid evolution of social media networks over the last few years, influencer marketing has been evolved as a new marketing strategy. This is because today everyone has online access to market its products or services and influence the behavior of their followers. Celebrity endorsement was the original form of influencer marketing but in today's digital world, social content creators with a niche audience can offer more value to the brands. These people have dedicated and engaged groups of followers on social media and are known as social media influencers (Chen & Shupei, 2018).

According to Berger (2016) influencers are being perceived as more credible believable and knowledgeable and they found that about 82% of consumers are likely to follow the influencers' recommendations. Similarly, Johansen and Guldvik (2017) state that online reviews and friends recommending something in forums serve as influential marketing. While looking at how the items are being used in daily life, one tends to associate influencers with a certain type of people, normally a more influential crowd. Influencers use attractive content to show their love for product recommendations as they enjoy a similar status to celebrities and are considered more trustworthy.

Li, Xiong, Wang, Chen, and Xiong (2019) suggest that with the popularity of social media networks, exploiting the social relationship offers a reliable source to enhance the performance of the recommendation system. Therefore, social media influencers have the potential to improve the recommendation system by building trust relationships. In social media, the combination of the online social network and recommendation system has created many opportunities for businesses that consider the importance of influential marketing in marketing their products (Goanta & Spanakis, 2020). Another reason for increased sales derived from influencer marketing is the halo effect created by the influencers through their content (Tapinfluence & Nielsen, 2016). Moreover, Influencer marketing is cost-effective than traditional marketing and can lead to marketing innovation as well. At the same time, consumers would continually have opportunities to review the contents even after an influencer marketing campaign is done, which bring an on-going effect made by the campaign for companies.

3.3.2 Curator system

As mentioned in the introduction part, this paper seeks to set up a new framework to simplify the existing model and make an easy comparison between the original RS and RS with social media influencers. This paper proposes a user recommendation system that prototypes preference for both users and the items they involve simultaneously. Curators are the individuals who gather and arrange existing content and enrich it with extra personal insights including comments, reviews, or ratings in different forms, such as a tweet, blog posts, or photos. They usually have a certain level of expertise or influence as an opinion leader (Jianling, Ziwei & James, 2020).

Curators can help the users to discover new items, new connections, and the new collection by human power rather than only provides product information pages by algorithm. In the curation platform, users act as curators who collect and organize content by reviews, tagging, or ratings. By receiving updates from whom they follow, they are exposed to interesting items and curation decisions. For example, a Spotify user may follow other users by tracking their listening activities which can influence their decisions. Research shows that the power of human curation can better serve as an important component of modern recommendation systems to link users to items. Moreover, the element of human power in the curated recommendation system enhances the transparency and trust of the users(Dragovic, Madrazo Azpiazu, & Pera, 2018; Wang, Zhu, & Caverlee, 2020). Using one the most famous e-commerce platform, called Xiaohongshu, also known as RED. In the Xiaohongshu community, users and celebrities can share their life, product reviews and travel guides.

1 *Picture 1: Example of curator system: Xiaohongshu*

As can be seen in the picture above, the users are able to view the videos or blogs of other consumers or curators based on their previous browsing history or their followed channels on their the homepage.

Since the research of Sylvain & Jacques and a lot of other researches stated that users would have different perceptions towards expertise, other consumers, and celebrities. Therefore, two main types of the curator will be investigated in this paper, one is the curator that focuses on using human expertise, and another one is the influencer curator who focuses on using their popularity, to see how different the degree of users' perception of trust in the recommendation has been affected.

3.4 Trust Model

Trust is a complicated topic as it is a subjective indicator, which is hard to measure. Rotter (1967) defines trust as "a generalized expectancy held by an individual that the word of another…can be relied on." According to Komiak and Benbasat (2006), emotional trust and cognitive trust in recommendation agent significantly increase the customers' attention to take help from the recommendation agent to make a purchase decision. However, they further found that emotional trust plays a more important role beyond cognitive trust in consumers' attention to adopting RA. According to Komiak and Benbasat (2006), cognitive trust is defined as the rational expectations; a customer has about the capability of RA to provide useful product recommendations. It implies customers develop cognitive interest when they find valid and good reasons to trust. While emotional trust is a trusting behavior primarily motivated by a strong positive impact for the object such as sense of security or comfort (Komiak and Benbasat ,2006).

McKnight, Choudhury, and Kacmar (2002) have proposed a trust-building model for build-ing trust in e-commerce vendors. The model includes three perspectives; perceived website quality, perceived vendor reputation, and structural assurance i.e., consumers' perception of web environment safety. According to this study, all three factors significantly influence the consumers' trust in the web vendors. Particularly, the website reputation and quality are the critical factors that online vendors can use to overcome the negative perceptions and to build consumers' trust in the safety and security of the web environment. The findings of McKnight et al. (2002) have further extended by (Pavlou, 2003) who proposed the technology acceptance model (TAM) to explain that perceived usefulness and ease to use the website are key factors for e-commerce acceptance. This proposed model assimilates perceived risk and trust which are merged given the implied uncertainty of the online environment. Similar to McKnight et al. (2002) and McKnight et al. (2002), the trust in websites has been al-so supported by Sheng (2012) as a key driver to increase the customer trust in RA and RA's recommendations. He further found that consumer participation in using RA can also increase the customer interest in RA which in turn can increase their intentions to buy items based on RA's recommendations.

This study takes a trust-based, emotional approach to study Recommendation Agent adoption. Based on the trust literature and theory of reasoned action, this study critically examines the role of emotional trust in encouraging consumers to adopt RA in making purchasing decisions. The theoretical foundation of this study is drawn from the Theory of Reasoned Action (TRA). The relationship between emotional trust, cognitive trust, and purchase intention is well documented by the TRA framework (Fishbein & Ajzen, 1977).

Using TRA as a theoretical approach, the research model of this study illustrates the causal cycle from cognitive trust to emotional trust to use intention i.e., trusting intention to adopt RA for decision making. The existing literature considers the trust-related implications of both emotional factors i.e., institutional factors, and cognitive factors i.e, vendor-specific trustbuilding drivers (Komaik and Benbasat , 2006; McKnight et al. 2002). The vendor-specific factors include the reputation and quality of the website. The cognitive trust in integrity and competence of RA are the beliefs customer develop based on rational reasoning such as website quality and reputation. The institutional factors are the users' perception of the online environment that serves as an attitude and intention towards the behavior of RA adoption. Thus, emotional trust as an attitude is an evaluative effect from relying on RA and any increase in cognitive trust in integrity and competence will increase customer's emotional trust. Therefore, Trusting beliefs and trusting intention together means trust as has been stated by McKnight et al. (2002). Trust helps customers to overcome uncertainty and the risk perception.

On the other side, Komiak and Benbasat (2006) argued emotional trust is more important without which cognitive trust is inappropriate to examine how people make purchase decision. They argued that people's cognition abilities are overstated due to rational choice perspectives. Moreover, the rational choice perspective allows little emotional and social influence on trust decisions. Emotional trust is defined as a trusting behavior derived from the positively strong effect for the trust object (Komaik and Benba-sat ,2006). Based on the literature, this study conceptualizes the emotional trust as an attitude towards adoption of RA as it is an evaluating effect for relying on RA. According to TRA, attitude is the major factor behind the person's intention to perform a specific behavior. In the case of RA adoption, high cognitive trust in the competence of RA means that customers perceive that relying on recommendation agents will provide well-customized recommendation. This suggests that cognitive trust is interlinked with the emotional trust and any increase in emotional trust is derived by the cognitive trust in competence and integrity of RA. To simplify, a positive attitude towards purchasing behavior will lead to the purchase intention i,e., customers tend to adopt an RA when they will have a high level of emotional trust. Moreover, the way emotional trust complements the cognitive trust provides the clear understanding of trust intention and RA adoption. Therefore this study uses emotional trust i.e., trusting intention as a major driver to the adoption of recommendation agent.

4. Conceptual Framework

4.1 Curator Systems

Sub. Question 1: Are the recommendations from the curator system more acceptable by users?

The introduction of curator systems in general recommendation models could potentially influence the users' acceptance rates of related suggestions due to certain attributes of the framework. There are features of a recommendation system that integrates curators that would boost its appeal and therefore recommendations given. Specifically, we consider the following: curator system vs general recommendation, perception of trust, type of curator and transparency. Curator based systems would integrate sophisticated algorithms which make theoretical considerations for the users want of the same content. Essentially, they create social context for interactions, given that humans associate with things based on their perceived meaning (Chipp et al., 2018). A general recommendation system on YouTube for example, would suggest a link with no additional information, while a curator system not only offers a link of curated content but also ideas on what services or products to purchase.

There are many factors that influence users' acceptance rate of underlying recommendation systems with its architecture being key, with regards to either collaborative filtering or contentbased methods used to determine likely user preferences. Curator systems would offer enhanced integration of users' preferences and a more personal touch which directly influences trust levels of resulting recommendations. This takes form in one of three approaches, where the first uses social networks and browsing history to create a crowd curated environment with users as the curators. Alternatively, the basis of determination could be user information collected overtime that is ultimately managed by them or a combination of user-based and traditional collaborative filtering to improve efficiency of a recommendation system (Dragovic, Azpiazu & Pera, 2018). Organizations are exploring the additional value that infusing a more personal touch into their content and marketing strategies yields on their revenue generation, especially in more service-based industries.

Implementation of curators into general recommendation systems on a wider scale would provide tangible evidence of their effect on acceptance rate through positively affecting purchase intention and related features.

Consumers that use a curator system have more control over the suggested content, with the premise being their personal preferences, essentially curator-based recommendation systems do not take on the role of curator. This is part of their appeal, as consumers in the current market are overloaded with information and may question whether advertisements are based on their tastes or organizations with a wide advertisement reach. The opinions of community users make suggested services or items feel more authentic and narrows down selection to a set of relevant items from an extensive set of choices. Part of the curator system's viability is based on the algorithm applied in making predictions, with flexibility based on feature attributes enabling tailoring to better suit the dataset and analysis required. Recommender systems success metrics are dependent on these measures, where higher model accuracy makes it more likely that users will accept resulting recommendations (Herlocker et al., 2004). Essentially, curator systems are built on consumer behavior, with the added benefit of perceived expertise authenticating the process and suggestions. We therefore expect the following:

H1: Customers who use a curator system would have higher acceptance rate of its recommendations offered than the general recommendation system.

4.2 Trust

Sub. Question 2: Will the use of curator enhance the trustworthiness of the automatic recommendation system?

Curator systems could help to alter the users' perceptions of trust, as they bridge a platform of engagement essentially mediating a relationship between the type of systems and willingness of accepting recommendations. This is modelled after a mediation hypothesis theory, which would explain the effect that trust perceptions have on user acceptance rates through examining the effect that an underlying variable would have on the process. Essentially, the introduction of a curator in traditional recommendation systems is expected to influences users perceptions of trust in the preliminary stages of the process of mediating trust. This is because choice is driven by a calculated decision based on perceived advantages, where a trustor is more likely to cooperate after reasons to do so have been established (Komiak & Benbasat, 2006). Consequently, curator systems application is expected to positively influence recommendation perceptions from users, as it establishes a strong cognitive trust basis, which is elemental for emotional trust connections.

Emotional trust helps to bridge a trust gap that cognitive processes cannot due to the nature of e-commerce landscapes, as it helps to alleviate concerns such as uncertainty about the attributes and traits of the vendors they interact with. Given how difficult it is to establish trust on virtual platforms, curator systems would bridge this gap as they integrate the more personal aspects of social media with business elements of e-commerce. They would therefore help in positive perceptions of recommendations by providing relevant yet personal interactions with and suggestions to users. Trust helps consumers translate their feelings into actions, due to the feelings of security associated with the object at hand which allows steps to be taken despite the risks involved (McKnight, Choudhury & Kacmar, 2002). Curator based systems are therefore expected to make elemental differences in preliminary interactions between users and vendors or e-commerce sites, that positively influences their decisions on whether to use the services in future. Given the inherent risk associated with online shopping platforms such as privacy, quality restriction and intention of advertisement, the role of trust is more prevalent than ever.

Influencers have been found to be more believable than traditional automated systems due to the proven integration of human complements into the process, and would form part of the curator eco-system. Curator systems are expected to positively affected purchase intentions as consumers are more likely to positively perceive attributes such as benevolence, reputation and privacy concerns present in traditional systems. Research on related issues support the notions, with close to 60% of purchase intention being linked to trust (Oliveira et al., 2017). The introduction of curator systems incorporates not only the users' preferences but an eco-system of similar beliefs managed by a trusted platform, which positively influences the recommendations finally presented. The risks and concerns present in e-commerce platforms are especially challenging to overcome due to the lack of personal interaction with consumer, CS would significantly help. In order to examine this effect, the mediator role of trust needs to be first tested:

H2: Trust mediates the relationship between willingness to accept the recommendations and the types of system used.

4.3 Curator Types

Sub. Question 3: Will the types of curator affect users' perception of trustworthiness of the recommendations and how?

The type of curator involved with the process is fundamental in establishing a robust framework which could either generate substantial and positive engagement and conversion or underwhelming results. This is the result of the social relationship designed and ultimately generated by curators, who in the modern business age are in charge various steps such as designing delivery systems from technical perspectives, or managing the content released in the market through influencer strategies for example. Ultimately, even in instances where suggestions are purely digital, consumers still apply human social rules and expectations to computers (Qiu & Benbasat, 2009). In automated models, the informational disparity humanness of the system is a key factor in enhancing the quality of recommendation systems and ultimately acceptance rates. Consequently, the type of curator system implemented becomes elemental in determining the level of acceptance resulting suggestions elicit from consumers with complaints of innately robotic capabilities for exampling generating low engagement.

4.3.1 Curator Popularity

We present curator popularity as a fundamental factor in influencing purchase intention given that visibility is as important in the current business environment. The popularity of curator system and related personnel is important in generating a high acceptance rate among users with there being tremendous power in numbers. The trendier items and services suggested are, and the person making these recommendations are the more likely that consumers purchase suggested items. Consequently, the reach that related systems have should be enhanced through well deliberated and designed systems. Google is an example of a curator that manages its information in similar fashions, where the most popular content is fashioned rather than the most relevant, which has resulted in the organization having the most inbound links. Certain curator suggestions are likely to foster more support owing to noted market popularity and acceptability, with book sites like Goodreads for example basing recommendations on activity generated by underling products (Wang, Zhu & Caverlee, 2020). The popularity of curators and the effect on acceptance is an interesting relationship, with high engagement and acceptance rates feeding the following expectations:

H3a: The popularity of curators is positively related to user's intention of accepting the RS's/CS's recommendations.

4.3.2 Curator Expertise

The factor of curator expertise also affects acceptance rates where we suggest that the more provenly established a curator or related systems are, the more acceptable its recommendations are to users. The users are more sensitive to misinformation and more likely to withdraw support from connected organizations, which makes how knowledgeable curators and related systems are key in generating positive engagements. Consequently, preliminary specialization should be integrated into the framework, with a proven level of expertise expected to generate more trust from users with regards to recommendations. The source of recommendations is a fundamental factor in determining whether or not users trust information from certain sources, with a distinction of personal or impersonal ties aiding users to make decisions. This is because the sources lead to personal or impersonal recommendations which are either helpful or detrimental to acceptance (Kunkel et al., 2018). Furthermore, consumers are more interested than ever on ethics and the veracity of information disseminated by organizations. Consequently, curator-based systems that are better received and more popular in the market are often backed by verifiable source and a certain level of expertise. Thus, we expect the following:

H3b: The expertise of curators is positively related to user's intention of accepting the RS's/CS's recommendations.

4.4 Transparency of the Recommending Process

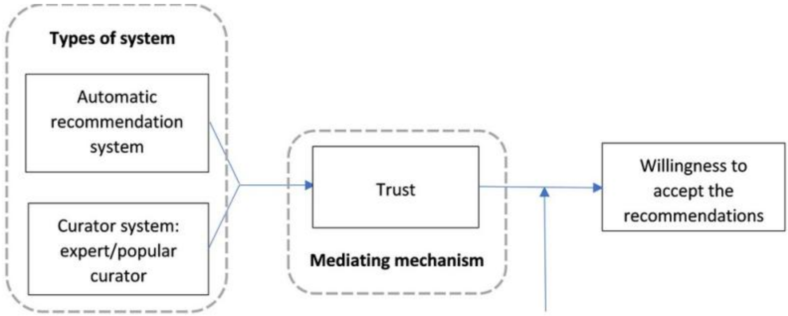
Sub. Question 4: Will the transparency of the recommending process of the system increase user's perception of its credibility, therefore also enhance users' willingness to accepting the recommendations?

How transparent a recommendation or curator system is could either positively or negatively affect how users perceive and therefore react to suggestions. The issue of transparency of recommendation systems is gaining traction, with users being more apprehensive on interacting with certain organizations and platforms due to privacy concerns. This is due to the significant knowledge gap on how organizations collected and utilize information through interactions on digital platforms. This breeds grounds for related developments as a means of fostering trust and long-term engagement in recommendations and with related curator systems (Vorm & Miller, 2018). Organizations have discovered links between the performative aspects of similar structures and perceived trust, fostered through activities that enable end users to better understand the processes guiding the organization.

Steps such as designing and implementing system-generated response programs that justify why certain recommendations have been made provides users with the logic behind suggestions and increase the likelihood of acceptance. The results mirror similar studies that show system explanations increases trust levels, consumer understanding, enhances better detection and error handling and calibrates a healthy degree of reliance on predictive aids. Transparency is further enhanced through providing certain types of information to users as an alternative to justifications as this requires robust analytical structures, with issues of subjective definition of a good explanation presenting additional challenges. Examples of transparency models to consider include but are not limited to actor model which reveal the source of information and transparency depth pyramids which explore data, process and policy transparency foundations (Hosseini et al., 2017). Through integrating these models into recommendation and curator systems, organizations enhance the quality of relationships fostered with users and therefore increase likelihood of positive reception.

The current business environment is also fraught with social activism, with consumers examining the underlying principles that govern the organization, with apprehension of transparency being a troubling sign. Essentially, organizations enhance the data exchange process through giving the users more control in form of transparency, with consumers being relatively worried about how their personal data is used with 97% of participants of a survey citing concerns on misuse of personal data (HBR, 2015). Transparency is therefore important for not only establishing trust but also rationalizing the product or service quality that users receive. A release of different sources of information used to guide curator or recommendationbased systems could directly influence whether or not consumers accept suggestions. Selfreported data is for example valued less than digital exhaust whereas profiling data is the most valuable. While increased transparency might leave the organization vulnerable, they may also have a positive impact on overall engagement and results, therefore leading to the following expectations:

H4: Higher transparency of recommendation process systems strengthens the relationship between perception of trust and the willingness to accept recommendations



2*Picture 2: conceptual model*

As the visual representation of the model (picture 2) shows, this research investigates how different types of recommendation system could increase users' perceived trust, which ultimately influence users' willingness of accepting the recommendations. Then it will also investigate into one important factor that might affect the relationship between trust and recommendation acceptance, transparency of the recommendation process.

5. Methodological framework

ContentIn order to determine the effect of curators on the trustworthiness of recommendation systems, this paper takes the users' willingness to accept the recommendations that are given by the RSs as the dependent variable, and uses the perceived trust and transparency of RS's recommending procedure by users as the independent variables. This study ran with the help of an experiment sketch via an online survey with 3x2 between-subjects design to test these variables and verify hypotheses. To facilitate subsequent data analysis, the questionnaire used randomized controlled trial(Chalmers at el., 1981), participants were allocated to different comparison groups. In the section, the research methods used and its launching procedure are being described in depth. Firstly, the data collection strategy and sample strategies are outlined with short explanations of why they have been used. Followed by the measure used to gather data to illustrate what is being measured and how it has been measured.

5.1 Data collection and Sampling strategy

This thesis intends to conduct field research in form of questionnaires since an online experimental design provides the ease of accessing the participants and low implementation difficulty among the limited time and conditional constraints. The first step to collect primary data is to determine the sampling method. The participants were selected by using a nonprobability convenience sampling approach with the central limit theorem. Therefore, at least 150 participants are needed for completing this research.

The next step is to design the questionnaire. In addition to the introductory text, the first part of the questionnaire is a given scenario to the subjects. The respondents got informed that they are considering to buy a new mobile and looking for a trustworthy purchase option through a recommendation platform. Respondents randomly received one of three recommendations prototypes offered by two kinds of aforementioned systems and in the curator system, this paper examines two different types of curator, which are named

Fashnetic and Devicnetic. Devicnetic gives a recommendation based on her/his expertise, and Fashnetic is based on her/his fame. The assigned recommendations were described as the platform's provided solution to users (respondents), which represented in video form created by Adobe Photoshop. Afterward in the survey asked participants their intention to accept the offered recommendations.

In the second part, this paper also used the between-subjects method for the moderator. Therefore, apart from the recommendations deduced by different RSs, the respondents were also randomly allocated to two groups. These two groups received the same survey arrangement only with slight differences on users' perceived transparency of the recommending procedure, thereby producing a measurable variance in perceived transparency and further study the moderating effects of transparency on recommendations accepting intentions. Half of the respondents would perceive an intimation of relatively high transparency on recommendation procedure, such as how were the recommendations made by the recommendation system. Another half would conversely perceive relatively low transparency.

Thirdly, to test whether the mediating role of trust exists, this research combined and streamlined the trust testing methods that have been proven in previous papers. As mentioned in the literature review, this paper only focuses on users' trusting intention, since trusting beliefs will lead to users' trusting intentions. Especially due to the consideration that lengthy questionnaires may reduce the attention of respondents and leads to dismissive answers. In the end, several demographic questions were raised, namely gender, age, and education level.

Additionally, with the aim of minimizing external influences on the results, many control variables are used in the design of the questionnaire. First of all, the background set in a single industry, which is the mobile phone industry. This industry was selected because it is relatively unisexual, meaning that males and females tend to have similar demands and interests. Moreover, the curator profiles were self-created, which prevents the respondents' bias due to their previous knowledge of existing influencers in several aspects, such as the number of subscribers, average views per video, a short background description, etc. Therefore, respondents have asked to rate the curator's popularity and expertise, and transparency of the recommending procedure to ensure whether the manipulations set successfully.

5.2 Measures

5.2.1 Trust

The trusting intention scales were employed originated from Dobing (1993) and have readopted by McKnight, Choudhury, and Kacmar (2002). The scale consists of 4 items, and all these four items have been proved their validity in previous papers with relatively high factor loadings and reliability (Cronbach's alpha). Respondents were asked about their willingness to depend on the recommendations given by the Recommendation platform (Example item: "When I need advice for a purchase, I would feel comfortable depending on the recommendations provided by a recommendation platform").

5.2.2 Transparency

Respondents with higher transparency setting received a list of questions that ask about their preferences for mobile phones. Such as more concerning attributes, expected price, etc. In another case, nothing would be displayed before the suggestion given.

5.2.3 Control variables

It was controlled for five variables to exclude alternative explanations. First is the degree of expertise and popularity of curators, by asking respondents: "Please rate your perception of the popularity and the expertise of the curators who were presenting in videos" in a five-point Likert scale from low as 1 to 5 as high. The second one is respondents' perception of transparency of the procedure, by asking: "To what extend you think you know how the recommendation system works?" with a five-point Likert scale from fully aware as 1 to fully unaware as 5. Moreover, to prevent the customers from knowing the intent of the test in advance, the question for testing the manipulation has appeared at the end. Gender, age, and education level were included as control variables because they can affect attitudes (Chan, Taylor, & Markham, 2008; Spreitzer G. M., 1995). For instance, Gabriel & Gardner's (1999) results claimed that men tend to be more collectively interdependent, and women are usually more relationally interdependent.

They might have different preferences on popularity and expertise. M. Sutter and M.G. Kocher(2006) found out that trust increases as consumers' age increases. Besides, except gender was measured in nominal form, both age and education levels were designed in ordinal form. As age was ranged into 6 categories from under 18 to over 55.

5.3 Data analysis

This paper conducted a regression to find the extent of the impacts by looking at the path coefficients between the variables. To complete the analysis, preliminary data preparation and descriptive statistics were first required. After these two basic processing, manipulation check, reliability, and validity need to be tested to indicate the quality of the research design. Lastly, the previously established hypotheses are tested and analyzed in multiple stages.

5.3.1 Data preparation

Before the actual test, the raw data has been cleaned and converted to a format that the software could understand and handle. There were originally 160 participants. However, someone rated the curator's expertise and popularity exactly the same value. If the participants read the description of the curator carefully, it is almost impossible to happen. After excluding these participants, 154 participants were left. First of all, the level of recommending procedure transparency has been recorded as a binary variable. Respondents who answered the question on the preference list were deemed to be in a high-level transparency scene and coded as 1, low-level transparency scene as 0. Furthermore, the different recommendations randomly offered to respondents is a nominal variable. As nominal variables only offer plain text as information and do not offer any mathematical value, which is not suitable to use for a regression. Hence, they need to be recoded into dummy variables where one level acts as a baseline for other variables. The offered recommendations consist of three types (Official advertisement, Fashnetic, Devicnetic) where the Fashnetic and Devicnetic have been merged into one variable as both of these recommendations were belong to curator systems(CSs), and the traditional RSs acts as the baseline. In order to make the test operatable, the independent variable has been recoded as a dummy variable, represented as Curator System in tests and tables. When the received recommendation was provided by CSs(Fashnetic & Devicnetic), the value of the dummy is 1. When the received recommendation was provided by general RSs, the value of the dummy is 0.

5.3.2 Descriptive analysis

After the data was cleaned and coded, descriptive statistics have been conducted. The descriptive statistics show that 84 males and 70 females participated in the survey. With regard to age, it can be noticed that 76% of participants are between 18 to 34, and the group between 18-24 years share the highest percentage (46.8%), which due to the distribution channel that a student could have. Due to the same reason, most people also share the same education level. 72% of participants are Bachelor's or Master's students. Besides the demographic attributes, the average willingness of recommendation acceptance is 3.66 (SD = 1.211), above the median (M = 2.5). The average trusting intention is 14.16 (Max = 20, Min = 5), also above the median (M = 12.5). All these data mean that in this digital era, most respondents are still willing to accept the recommendation system to some extent.

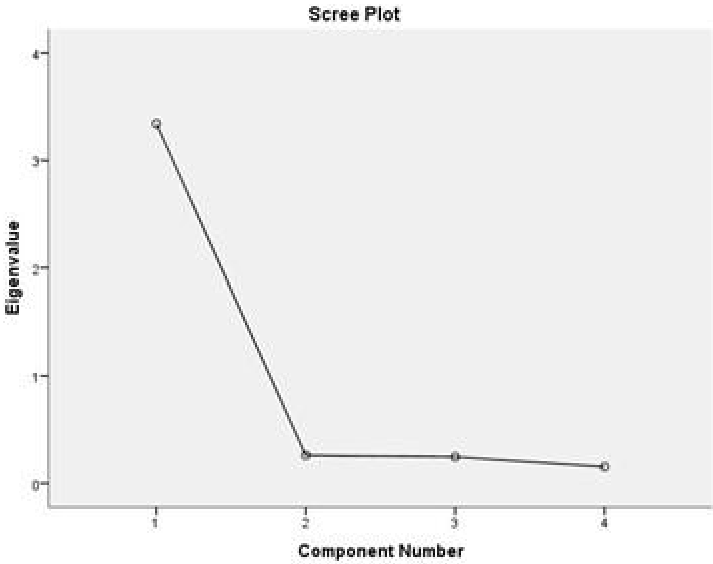
5.3.3 Reliability and validity

To ensure that the research design has sufficient quality, factor analysis was used to test the measurement model and established convergence validity of trusting intention. Convergence validity refers to the degree to which tests designed to measure a particular variable are actually measuring the underlying theoretical constructs because they share variance (Schwab, 1980). Reliability refers to the stability and internal consistency of the inevitable results of the measurement tools used. Simultaneously, internal consistency reliability, though usually considered necessary, fails to serve as a sufficient condition for convergent validity (Schwab, 1980).

There are four questions to test trusting intention which are included in the reliability analysis to test the reliability of internal consistency. It can be seen from the results that Trust’s Cronbach’s Alpha is 0.934, which is much greater than the 0.7 standards, so the overall scale has a good level of reliability. It can be seen from the results of Item-Total Statistics that the reliability index is not significantly improved after deleting each item, so it is further verified that its reliability level is good.

Since all four questions was towards trusting intention, it has to make sure that all these questions are belong to the same underlying concept. The principal component extraction method is used to perform factor analysis on Trust. The results showed that the KMO value was

0.856, and reached the significant standard of 0.001. The hypothesis that all the variables are independent is rejected, and the variables are considered to have a strong correlation. Therefore, the above topic is suitable for factor analysis. Further on, the principal components are extracted from the four questions of trust by using the method that the characteristic root is greater than 1. From the results in the table of factor analysis in the appendix, we can see that a total of 1 principal component is extracted from the four questions of trust, and the cumulative variance contribution rate is 83.509%, which means a high degree of information extraction and it fits to the previous design intention. In addition, the scree plot refers to a graph that shows how much information the factors cover in the factor analysis. Generally, it is steep first and the first factor covers the most information and then decreases sequentially, the trend line become flatter. In our scree plot, the trend line has dropped significantly after the first principal component, and the extracted factors can basically cover all the information of the original variable. Therefore, the scree plot supported the extraction of a principal component result.



3*Picture 3: Scree plot of factor analysis*

Use the maximum variance method to rotate the questions of the scale. It can be seen from the results that the factor loading on the principal component of the four questions is between 0.9210.899, which are all higher than the 0.5 standards, so the scale has appropriate construct validity.

5.3.4 Manipulation check

The manipulation checks for curators' expertise and popularity was tested by paired t-test approach, to see whether the means of two paired variables are significantly different. To check the success of perceived transparency manipulation, independent sample t test was adopted.

Using the research method of paired-sample t test, the difference between popularity and expertise of Fashnetic, and the difference between popularity and expertise of Devicnetic were tested. It can be seen from the results that respondents perceived popularity on Fashnetic has a significantly higher score than perceived expertise on Fashnetic($t = 10,221$, $p < 0.001$); and perceived popularity of Devicnetic has a significantly lower score than expertise of Devicnetic ($t = 10,221$; $p < 0.001$). It indicates that the manipulation of different types of curator was successful, Fashenetic (popularity based) has been perceived as with high popularity but low expertise and Devicnetic (expertise based) has been perceived as with high expertise but low relatively low expertise.

Perceived transparency manipulation check applied the method of independent sample t-test. Using the high-low-transparency grouping as the grouping standard, the differences in the transparency evaluated by respondents under different levels of transparency were tested. From the results, it can be seen that under the condition of low transparency, the respondents' perceived transparency score is significantly lower than the score of perceived transparency under the condition of high transparency, which is in line with the manipulation purpose.

5.4 Hypothesis testing

To test the hypotheses constructed in the conceptual model, this paper has conducted multiple linear regression analyses. This statistical technique analyzes the relationship between independent variables, dependent variables, mediators, and moderators. In the paper, gender, age, and education level are taken as control variables; the types of recommendation systems as independent variables, Trust as the mediating variable; the willingness of accepting the recommendations as the dependent variable, and conducted a three-step for both mediating effect by PRCOSS, moderator effect test by stepwise regression. Lastly, the effect of curator’s attributes on the model, namely expertise and popularity is tested by a simple regression. The results are represented in table 1, 2 and 3.

5.4.1 Hypothesis 1

To find out whether the customers who used CSs would have a higher acceptance rate of its recommendations that has been offered than the general RSs, a regression analysis was conducted. First of all, the result presented in Table 1 confirmed that there is a direct relationship between the types of recommendation system and the user’s willingness of accepting the recommendations offered by RSs. The types of recommendations given by different systems can significantly predict the willingness to accept: curator system (β = 1.0147, $p < 0.001$), which general recommendation system has been used as a baseline variable (β = 0). Moreover, the types of recommendation system (‘Curator System = 1’) has a positive coefficient, which indicates that getting curators involved in the recommendation system would bring a positive effect on user’s willingness of accepting the recommendations. Therefore hypothesis 1 is supported.

5.4.2 Hypothesis 2

In this research, the mediating effect analysis used a three-step regression method and conducted by the PROCESS plugin in SPSS, which is able to run the test at once, rather than run the regression step-by-step. Same as Baron and Kenny's 3-step approach (1986), PROCESS divides its test procedure into three steps. In the first step, it analyzed the direct relationship between the independent variables ‘Types of Recommendation systems’ to the dependent variable “Willingness of accepting the recommendations” to test whether the hypothesis holds, which has been already confirmed with hypothesis 1. The second step is to analyze the regression of the independent variables “Types of RSs” to the intermediary “Trust”. The third step is to analyze the regression of the independent variables “Types of RSs” on the dependent variable “Willingness of accepting the recommendations” behavior after adding the intermediary variable trust to test whether the hypothesis is valid. If the regression coefficient between the independent variable and the dependent variable after the intermediate variable is added in the third step is less than the regression coefficient between the independent variable and the dependent variable in the first step, it indicates that there is a mediating effect. In PROCESS, the type of mediating role could easily be examined by looking at the direct effect and indirect effect value of the independent variable on the dependent variable. If both effects are significant, the mediating variable plays a partial mediating role. If only the indirect effect is significant, the direct effect is insignificant, the mediating variable plays a fully mediating role.

	Willingness of accepting the recommendations	Trust	Willingness of accepting the recommendations			
variable	*coeff*	*t*	*coeff*	*t*	*coeff*	*t*
Control variables						
Gender	0.2494	1.382	0.2414	0.4601	0.1914	1.4761
Age	-0.1196	-1.3555	-0.3355	-1.308	-0.039	-0.6119
Education level -.0751		-0.7462	-0.3508	-1.1984	0.0091	0.1259
The independent variables						
Types of RSs 1.0147 (1: CSs ; 0: General RSs)		5.3255***	3.5816	6.4657***	0.1542	0.9962
Mediating variable						
Trust					0.2402	11.8733***
R^2	0.19		0.2351		0.5852	
F	8.7374***		11.4492***		41.7517***	
Note : *** P＜0.001, ** P＜0.01, * P＜0.05						

The mediating effect results of this study are shown in the table above: after controlled the gender, age, and education level, types of recommendation system (Curator system = 1) can positively predict User's willingness of accepting the recommendations significantly compare to general recommendation system, as general RSs was the baseline (β = 1.0147, p < 0.001). In the model with "Types of RSs" as the independent variable and "Trust" as the dependent variable, types of RSs can significantly positively predict trust (β = 3.5816, p < 0.001). In the model where "Type of RSs" is the independent variable, "Trust" is the mediating variable, and "Users' willingness to accepting the recommendations offered by recommendation systems" is the dependent variable, types of RSs has no significant predictive effect, but Trust can significantly predict the willingness to accept (β = .2402, p < 0.001). Besides, the direct effect of types of RSs on willingness to accept is insignificant (β = .154, p = 0.3208 > 0.05), and the indirect effect is significant (β = .860, p < 0.001).

Based on the above results, trust has played a significant and full intermediary role between types of recommendation systems and Willingness to accept the recommendations, which supported hypothesis 2 that trust mediates the relationship between willingness to accept the recommendations and the types of system used.

5.4.3 Hypothesis 3

In line with hypothesis 3, an independent regression has been conducted, which makes the result clearer to analysis. The results in Table 2 presents that although the expertise degree of Fashnetic and the popularity degree of Devicnetic did not significantly affect user's willingness to accept, both the popularity and the expertise of curators are positively correlated with user's willingness to accept the recommendations offered by CSs($\beta = .193$, $p < 0.001$; $\beta = .055$, $p = 0.026$; $\beta = .034$,$p = 0.213$; $\beta = .438$, $p < 0.001$). Hypotheses 3a and 3b for popularity and expertise of curators are therefore both supported. The reason the insignificant results happened might be the setting of the curator's characteristics. As Fashenetic set with a high level of popularity and a relatively low level of expertise, and the Devicnetic inversely set with a relatively low level of popularity and a high level of expertise. It brought the fact that user's willingness of accepting the Fashnetic is more based on the curator's fame. The user's willingness of accepting the Devicnetic is more based on the curator's expertise.

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1,272	,119		10,677	,000
Popularity of F	,193	,014	,480	14,244	,000
Expertise of F	,055	,025	,072	2,245	,026
Popularity of D	,034	,027	,050	1,250	,213
Expertise of D	,438	,017	1,068	25,712	,000
Gender	,054	,036	,033	1,495	,137
Age	-,006	,017	-,009	-,380	,704
Education level	-,067	,020	-,079	-3,325	,001

a. Dependent Variable: types of recommendation

Table 2: Relationship between the curator's expertise level and popularity level with user's willingness of accepting the recommendations

5.4.4 Hypothesis 4

To test hypothesis 4, a stepwise regression has been used to test the moderation effect of transparency between trust and users' willingness to accept recommendations. The first layer included gender, age, and education as control variables, the second layer included trust and transparency as independent variables and moderator variables; the third layer included interaction items of trust and transparency.

Types of recommendation system offers

Variable	Model 1	Model 2	Model 3
Control variables			
Gender	.135	.081	.092
Age	-.129	-.037	-.051
Educ	-.040	.009	.023
The independent variables			
Trust		.742***	.923***
Moderator variable			
Transparency		.022	.641***
Interaction			
Trust * Transparency			-.698***
R^2	.036	.583	.606
F	1.857	41.356***	37.684***
$\triangle R^2$	.036	.547	.023

4*Table 3: Moderating effect test*

As shown in Table 3 above, Model 1 represents the influence of control variables on the user's willingness of accepting the recommendations. It can be seen from the results that each control variable has no significant predictive effect on user's willingness to accept. Model 2 shows that Trust and Willingness of accepting the recommendations have a significant positive impact (β =.742, $p < 0.001$), while the moderator Transparency has no significant impact on Willingness of accepting the recommendations. Finally, the interaction term Trust * Transparency is introduced into the model, It can be seen from model 3 that after introducing the interaction term, the interaction term coefficient is significant ($\beta = -.698$, $p < 0.001$), The above analysis shows that Transparency has a significant moderating effect between Trust and user's willingness to accept the recommendations. However, the interaction term is negative, which means that higher transparency of the recommending process of the systems does not positively affect the perception of trust on the recommendation systems. Hypothesis 4 has been rejected.

6. Discussion

The invention of the automatic recommendation system brought more opportunities and efficiency for both customers and providers. Nevertheless, it also bore large trust issues due to its digital property. It has abandoned the trust between real person contacts. According to Nielsen's Global Trust Report on Advertising, 92% of consumers believe that suggestions from friends and family are more important than advertising (Nielson, 2012). At the same time, the rapid development of the Internet has also stimulated the rapid generation and rise of Internet celebrities. As supported in hypothesis 1, when a general automatic recommendation system included curators (influencers) into its system, consumer's willingness to accept the recommendations would be increased, which consisted with the result of previous researches that influencers are considered more credible and knowledgeable (Berger, 2016). Influencers themselves are consumers, users would have a sense of identity with the curators. Simultaneously, curators also share the function of celebrities, such as the halo effect common consumers would not have (Tapinfluence & Nielsen, 2016).

Trust is an important and fundamental element of consumer intention, especially in this era of the universal digital era. Such as intention to repurchase, intention to churn a subscription, or intention to accept the recommendations given by vendors, etc. With the adoption of RS, the relationship between RS and users is a state of dependence and this dependence will entail risk. Trust among two parties becomes very crucial (Chopra and Wallace 2003). The result of the mediation test in hypothesis 2 has shown that trust has a full mediation effect between RSs adoption and user's willingness to accept, which indicates that willingness of accepting the recommendations only happened due to user's trust in RSs and this conclusion has consisted with previous researches examined the same field.

Moreover, as inferred in the conceptual model, both the expertise and popularity of the curator have a positive effect on the willingness of accepting the recommendations, which means that both of them are important drivers for users to accept the offered recommendations. Under the deeper analysis of the data, the expertise level of curators has a larger impact on user's willingness to accept the recommendations than the curator's popularity. Although the smartphone industry is a relatively unisexual field, but because it is a technology based-product, the professional requirements for its function evaluation are relatively high. The consumer would concern more into the performance of smartphones and therefore it might cause the choice bias in the expertise-based curator from users. It has made the expertise of the curator seems more important for user's trust perception, but it depends on the industry that researches examine.

In marketing field, transparency is usually viewed very broadly as a trust building approach (Bentele & Seidenglanz, 2008; Donaldson & O'Toole, 2000; Sheppard & Sherman, 1998). However, the hypothesis is rejected and the result told that transparency is presenting a negative effect on trust. Similar results also happened in other papers. Such as in the paper of Audrey

However, the hypothesis is rejected and the result told that transparency is presenting a negative effect on trust. Similar results also happened in other papers. Such as in the paper of Audrey Portes, Gilles N'Goala, Anne-Sophine Cases (2020), they segmented transparency into multiple dimensions. They figured out that different dimensions of transparency might bring different effects on consumers' trust in a particular field. Further analysis indicated that there is a potential quadratic U-shaped relationship between transparency and trust, which means that out of certain threshold, transparency would lose its effectiveness in enhancing trust. Apart from that, people have limited rationality. Overly or complex additional information instead of induce reassuring, would generate new uncertainties that can induce negative effects (Lowrey, 1998). For instance, when users know how the recommendation system works, they may start to doubt on the usage of their information.

Additionally, age, gender, and education level differences didn't demonstrate any significant impact on their trusting intention and the willingness of accepting the recommendations, which was not expected. It might due to the homogeneity of the collected samples.

6.1 Implications

This research provides managers with better insights and enables them to understand whether the participation of curators could more effectively increase users' trust in the automatic recommendation system. So that their acceptance of recommendations from online systems increases. According to hypothesis 2, trust plays an important role in consumers' intention to actually take the recommendation into their consideration or even buy products from the recommendation. Therefore, vendors, social media, and influencers, all should focus more on how to increase their trustworthiness towards consumers. Inspired by hypotheses 1, 3, several approaches could use to increase consumer perceived trust in RSs.

Firstly, with the rising of the Internet celebrity economy, many brand managers and advertisers are already striving to find excellent influencers to achieve advertising effects. To further develop the strategy with our findings, the managers of all kinds of the platform that uses automatic recommendation systems should try to foster their own curators, which would attract more business chances from product providers. Secondly, hypothesis 3 confirmed that high popularity and high expertise could both enhance users' intention to trust into the RSs. Therefore, when brand managers premeditate on which curator would be the best choice to promote their products, they should consider these two attributes. In addition, these findings also prove that the different characteristics of curator will also bring different impacts. Brand managers should choose collaborators according to the attributes of their respective companies.

All in all, these contributions could bring benefits and opportunities to both recommendation vendors and merchants who could like to take advantage of the automatic recommendation system.

6.2 Limitations

This study entails several limitations that could hamper the validity and representativity of the results. First of all, the research was conducted in an online survey form, and it was almost impossible to control external interference. Interference caused by external factors might affect the experience and the answers to the questionnaire. Besides, most of the surveys are predesigned by the questionnaire designer to answer the scope, making the respondent more limited in answering the survey, which might cause a miss of more detailed and in-depth information. In addition, online surveys constrained the possibility of actual interaction between the respondents and prototyped RSs. It would affect the authenticity of responses or provides a wrong perception that the researcher wanted to get manipulated. At the same time, all measures were distributed in English, which may have caused difficulties for non-native English speakers.

Secondly, the central limit theorem sampling approach only required the minimum number of respondents. At the same time, due to the convenience sampling method, the sample mainly entailed respondents from the university, which consisted mostly of age group 18-34, and had bachelor's degree or master's degree. This may lead to serious deviations in the data. Moreover, as the participants are highly educated, they might realize the intention behind the survey. Therefore, the feasibility of extrapolating the results to the general population was questioned.

Thirdly, due to the time and length of the questionnaire, this research only used trusting intention to represent the larger concept: "trust" which is not comprehensive enough.

6.2.1 Further research

As mentioned in the limitation section, this paper only focused on trusting intention which is not comprehensive enough to present the whole concept “trust”. According to the result of hypothesis 2, trust is a strong mediator towards consumer’s willingness to accept the recommendations have been provided or showed. Moreover. trust is also a very complicated topic, and hard to measure of being a subjective variable. In the future, researcher could examine trust more in-depth with more dimensions. The moderation test was failure, but there still space to improve. Furthermore, there are many more elements that would have impact on the relationship between user’s acceptance on RSs and the RSs itself can be investigated.

Furthermore, lacking of trust does not only induce rejection on accepting the recommendations, also consumer’s privacy concerns. Consumers questions about the usage of the recorded information they offered consciously and even unconsciously, which leads to a unwillingness of providing information, giving trust and consider the recommendations provided. It’s one of the biggest issue in online commerce environment. Researcher could also work on this direction towards RSs for future investigations.

According to the unexpected find out on transparency in this paper and other papers, transparency might have different impacts on people’s trusting intention could be a large topic and interesting that worth to investigate.

In addition, if future investigators are interested in the intervention of Internet celebrity economy in RSs, the attributes of curators also not just limited with their expertise and popularity. It is also noteworthy to look into other dimensions.

7. Conclusion

The purpose of this paper is how could people's trust in the recommendation systems(RS) be enhanced by looking at consumer's willingness of accepting the recommendations provided by RSs. First of all, we confirmed that trust is the key element in this relationship. In order to increase the trustworthiness, the use of RSs involved one of the most popular derivatives in the current online world - net influencers to be part of the system. The results show that influencers would be a powerful tool for many businesses and platform vendors. With collaboration with appropriate influencers, such as fit to the industry theme, brand competence, the influencers fame impact, etc., would largely increase the trust in automatically offered recommendations, gives a larger possibility that consumer would at least take the recommended product or brand into consideration set and learned more relevant information about them, which bring benefit to companies. For the platforms(e-commerce, social media, third-party recommendation sites, etc.), foster own influencers would provide much more business opportunities, improves its visibility and influence. Moreover, as a consumer, the new system could provide you information overload reduction, an advance evaluation made by other influential consumers before purchasing and trust. In conclusion, the adoption of the "curator system" would promote, purify, and beautify the online shopping environment.

8. Appendix

8.1 Descriptive analysis

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	84	54,5	54,5	54,5
	Female	70	45,5	45,5	100,0
	Total	154	100,0	100,0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18 - 24	72	46,8	46,8	46,8
	25 - 34	45	29,2	29,2	76,0
	35 - 44	14	9,1	9,1	85,1
	45 - 54	21	13,6	13,6	98,7
	Over 55	2	1,3	1,3	100,0
	Total	154	100,0	100,0	

Educ

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than high school	2	1,3	1,3	1,3
	High school graduate	17	11,0	11,0	12,3
	Some college	21	13,6	13,6	26,0
	Bachelor's degree	83	53,9	53,9	79,9
	Master's degree	28	18,2	18,2	98,1
	Doctorate	3	1,9	1,9	100,0
	Total	154	100,0	100,0	

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Willingness of accepting	154	1	5	3,66	1,211
Trust question 1	154	1	5	3,61	,979
Trust question 2	154	1	5	3,56	1,016
Trust question 3	154	1	5	3,50	,985
Trust question 4	154	1	5	3,49	,985
Trust	154	5,00	20,00	14,1623	3,62358
Valid N (listwise)	154				

8.2 Reliability test

Table Reliability Statistics

Cronbach's Alpha	N of Items
.934	4

Table Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Trust question 1	10.55	7.700	.823	.921
Trust question 2	10.60	7.378	.855	.911
Trust question 3	10.66	7.676	.821	.921
Trust question 4	10.67	7.439	.879	.903

8.3 Manipulation check

8.3.1 The perceived Expertise and popularity on curators

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Popularity_F	4,12	52	,983	,136
	Expertise_F	1,79	52	1,126	,156
Pair 2	Popularity_D	2,10	51	1,153	,162
	Expertise_D	4,14	51	,693	,097

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	Popularity_F Expertise_F	2,327	1,642	,228	1,870	2,784	10,221	51	,000
Pair 2	Popularity_D - Expertise_D	2,039	1,232	,173	-2,386	-1,693	-11,818	50	,000

8.3.2 The perceived transparency level in two conditions

Group Statistics

	Trans	N	Mean	Std. Deviation	Std. Error Mean
Trust	low transparency	76	13.4342	3.31194	.37991
	high transparency	78	14.8718	3.79117	.42927

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Trust	Equal variances assumed	1.609	.207	-2.503	152	.013	-1.43758	.57424	-2.57211	-.30306
	Equal variances not assumed			-2.508	150.235	.013	-1.43758	.57323	-2.57023	-.30494

8.4 Factor analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.856
Bartlett's Test of Sphericity	Approx. Chi-Square	515.382
	df	6
	Sig.	.000

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.340	83.509	83.509	3.340	83.509	83.509
2	.260	6.502	90.011			
3	.246	6.151	96.162			
4	.154	3.838	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix

	Component
	1
Trust question 1	.900
Trust question 2	.921
Trust question 3	.899
Trust question 4	.934

Extraction Method: Principal Component Analysis.

8.5 Mediating effect test

variable	DV		Trust		DV	
	coeff	*t*	*coeff*	*t*	*coeff*	*t*
Control variables						
Gender	.2494	1.3820	.2414	.4601	.1914	1.4761
Age	-.1196	-1.3555	-.3355	-1.3080	-.0390	-.6119
Educ	-.0751	-.7462	-.3508	-1.1984	.0091	.1259
The independent variables						
OvsDF	1.0147	5.3255***	3.5816	6.4657***	.1542	.9962
mediating variable						
Trust					.2402	11.8733
R^2	.1900		.2351		.5852	
F	8.7374***		11.4492***		41.7517***	

Note：*** $P<0.001$，** $P<0.01$，* $P<0.05$

8.6 Popularity and expertise effect test

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,272	,119		10,677	,000
	Popularity of F	,193	,014	,480	14,244	,000
	Expertise of F	,055	,025	,072	2,245	,026
	Popularity of D	,034	,027	,050	1,250	,213
	Expertise of D	,438	,017	1,068	25,712	,000
	Gender	,054	,036	,033	1,495	,137
	Age	-,006	,017	-,009	-,380	,704
	Educ	-,067	,020	-,079	-3,325	,001

a. Dependent Variable: types of recommendation

8.7 Moderating effect test

variable	DV Model 1	Model 2	Model 3
Control variables			
Gender	.135	.081	.092
Age	-.129	-.037	-.051
Educ	-.040	.009	.023
The independent variables			
Trust		.742***	.923***
moderator variable			
Transparency		.022	.641***
Interaction			
Trust * Transparency			-.698***
R^2	.036	.583	.606
F	1.857	41.356***	37.684***
$\triangle R^2$	.036	.547	.023

8.8 Questionnaire

Variable		
Willingness of accepting	1. To what extent you have the intention to accept the recommendations that were given in the survey, based on your preferences and historical footprints?	
Trusting intention	2. When I need advices for a purchase, I would feel comfortable depending on the recommendations provided by the recommendation platform 3. When facing difficulty making a choice, I would follow the recommendation(product) backed by the recommendation platform 4. I feel that I could count on the platform, it would act in my best interest. 5. If I need more suggestions for another purchase, I would want to use the platform again.	
Manipulation check – expertise & popularity	6. Please rate your perception of the popularity and the expertise of the curator who was presenting in video	
Manipulation check – Transparency	7. To what extent you think you know how the recommendation system works?	

8.9 Recommendation prototype & Curators profiles

Official advertisement:

Here are the recommended video provided for you by the platform:

It is an official company advertisment with general product information

Fashnetic:

Just in case you want to know more about the video uploader, here we provide some extra info of the uploader. (Respondents please carefully read the following information)

Channel name: Fashnetic
Number of subscribers: 7,7 mln. subscribers
Average views: 1.651.143 views per video
Number of video she posted about smart device category: 3 out of 87
Average comments: 30,158
Background: This video creator has a multi-theme channel, which means she presents different themes of video, but mainly attach in fashion field, especially she is a part-time model. Sometimes she shares her daily outfits, make-up products she uses, her travels, her daily life etc.

Devicnetic:

Just in case you want to know more about the video uploader, here we provide some extra info of the uploader. (Respondents please carefully read the following information)

Channel name: Devicnetic
Number of subscribers: 237K subscribers
Average views: 346,219 views per video
Number of video he posted about smart device category: 68 out of 75
Average comments under videos: 3,956
Background: This video creator's channel mainly focus on smart devices, he does evaluations of new products of various smart device brands. He started to be a content creator 3 years ago as a part-time career based on his mobile phone shop owner experiences.

8.10 High transparency scene

Take 3 attributes that you take into consideration the most when you choosing a mobile phone?

Appearance	Storage space
Speed	Battery life
Size	Signal
Price	Compatibility
Speakers & Microphones	Screen duration and quality
Camera quality	Color

Between which range of price do you expect?

- €0-200
- €200-400
- €400-600
- €600-800
- €800-1000
- Above €1000

How would you rate your knowledge about IT products?

0	1	2	3	4	5	6	7	8	9	10

Click to write Choice 1

9. Reference

- Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. Journal of retailing, 91(1), 34-49.
- Agler, Robert, and Paul De Boeck. "On The Interpretation And Use Of Mediation: Multiple Perspectives On Mediation Analysis". Frontiers In Psychology, vol 8, 2017. Frontiers Media SA, DOI:10.3389/fpsyg.2017.01984.
- Audrey P., Gilles N. & Anne-Sophie C. (2020). Digital transparency: Dimensions, antecedents and consequences on the quality of customer relationships. Recherche et Applications en Marketing 2020, Vol. 35(4) 72 – 98. DOI: 10.1177/2051570720973548
- Barry B., (2016) Referral marketing: Harnessing the power of your customers. Business Horizons, Volume 59, Issue 1, January–February 2016, pp. 19-28. https://doi.org/10.1016/j.bushor.2015.08.001
- Bach, T. M., da Silva, W. V., Souza, A. M., Kudlawicz-Franco, C., & da Veiga, C. P. (2020). Online customer behavior: perceptions regarding the types of risks incurred through online purchases. Palgrave Communications, 6(1), 1-12.
- Bentele G and Seidenglanz R (2008) Trust and credibility – Prerequisites for communication management. Public Relations Research. VS Verlag für Sozialwissenschaften, pp. 49–62
- Berger, J., & Keller Fay Group (2016). Research shows micro-influencers have more impact than average consumers., Retrieved from: https://www.expertvoice.com/wphttps://www.expertvoice.com/wp-content/uploads/2016/12/Power-of-Influence-Quantified.pdfcontent/uploads/2016/12/Power-of-Influence-Quantified.pdf
- Bo X. & Izak B. (2007), E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact. Management Information Systems Research Center, University of Minnesota MIS Quarterly, Vol. 31, No.1, pp. 137-209.
- Calhoun, C. S., Bobko, P., Gallimore, J. J., & Lyons, J. B. (2019). Linking precursors of interpersonal trust to human-automation trust: An expanded typology and exploratory experiment. Journal of Trust Research, 9(1), 28–46. doi:10.1080/21515581.2019.1579730

- Carmon, Z., Klaus W., & Marcel Z. (2003), “Option Attachment: When Deliberating Makes Choosing Feel like Losing,” Journal of Consumer Research, 30 (June), pp.15-29.
- Chalmers TC, Smith H Jr, Blackburn B, Silverman B, Schroeder B, Reitman D, Ambroz A (1981). "A method for assessing the quality of a randomized control trial". Controlled Clinical Trials. 2 (1): 31–49. doi:10.1016/0197-2456(81)90056-8
- Chan, Y. H., Taylor, R. R., & Markham, S. (2008). The role of subordinates' trust in a social exchange-driven psychological empowerment process. Journal of Managerial Issues , 20 (4), 444-467.
- Chipp, K., Strandberg, C., Nath, A., & Abduljabber, M. (2017). Content Curatorship and Collaborative Filtering: A Symbolic Interactionist Approach. Back To The Future: Using Marketing Basics To Provide Customer Value, 705-715. https://doi.org/10.1007/978-3-31966023-3_228
- Chen, L. & Shupei, Y., 2018. Influencer Marketing: How Message Value and Credibility Affect Consumer Trust of Branded Content on Social Media. Journal of Interactive Advertising 19(1):1-45. DOI: 10.1080/15252019.2018.1533501
- Chopra, K., and Wallace, W. A. "Trust in Electronic Environments," in Proceedings of the 36th Hawaii International Conference on System Sciences, IEEE Computer Society Press, Los Alamitos, CA, 2003.
- Donaldson B and O’Toole T (2000) Classifying relationship structures: Relationship strength in industrial markets. Journal of Business & Industrial Marketing 15(7): 491–506.
- Dragovic, N., Madrazo Azpiazu, I., & Pera, M. S. (2018). From Recommendation to Curation: When the System Becomes Your Personal Docent.
- Dragovic, N., Azpiazu, I., & Pera, M. (2018). From Recommendation to Curation. In IntRS Workshop. Vancouver. Retrieved 11 December 2020, from http://ceur-ws.org/Vol2225/paper6.pdf.
- Festinger L (1957) A theory of cognitive dissonance. Stanford University Press, Stanford
- Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research.
- Gabriel, S. , & Gardner, W. L. (1999). Are there ‘his’ and ‘hers’ types of interdependence? The implications of gender differences in collective versus relational interdependence for affect, behavior, and cognition . Journal of Personality and Social Psychology, 77, 642-655 .
- Gefen D., E. Karahanna and D.W. Straub (2003) "Trust and TAM in Online Shopping: An Integrated Model" MIS Quarterly, (27)1, pp. 51-90.

- Goanta, C., & Spanakis, G. (2020). Influencers and Social Media Recommender Systems: Unfair Commercial Practices in EU and US Law.
- Graeme A. Haynes(2009), "Testing the boundaries of the choice overload phenomenon: The effect of number of odxptions and time pressure on decision difficulty and satisfaction", Psychology & Marketing Volume 26, Issue 3. DOI: https://doi.org/10.1002/mar.20269
- Gustavsson, M., & Johansson, A. (2006). Consumer Trust in E-commerce. The Department of Business Studies of Kristianstad University. Retrieved from: diva-portal.org
- Hamelink C. J., (2001). The Ethics of Cyberspace. Sage Publications, Thousand Oaks, CA.
- Harvard Business Review (HBR). (2015). Customer Data: Designing for Transparency and Trust. Harvard Business Review. Retrieved 11 December 2020, from https://hbr.org/2015/05/customer-data-designing-for-transparency-and https://hbr.org/2015/05/customer-data-designing-for-transparency-and-trust?ab=at_articlepage_whattoreadnexttrust?ab=at_articlepage_whattoreadnext.
- Hee-Woong K., Sumeet G. & So-Hyun L. (2013).Examining the Effect of Online Switching Cost on Customers' Willingness to Pay More. Asia Pacific Journal of Information Systems Vol. 23, No. 1.
- Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. ACM Transactions on Information Systems, 22(1), 5–53. doi:10.1145/963770.963772

  Hosseini, M., Shahri, A., Phalp, K., & Ali, R. (2017). Four reference models for transparency requirements in information systems. Requirements Engineering, 23(2), 251-275. https://doi.org/10.1007/s00766-017-0265-y
- Huiping, W. & Shing, O. L. (2017). Can Likert Scales be Treated as Interval Scales?—A Simulation Study, Journal of Social Service Research Volume 43, 2017 - Issue 4, DOI: https://doi.org/10.1080/01488376.2017.1329775
- Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. Egyptian Informatics Journal, 16(3), 261-273. doi: https://doi.org/10.1016/j.eij.2015.06.005
- Izak, B., Weiquan, W., (2005). Trust In and Adoption of Online Recommendation Agents. Journal of the Association for Information Systems Vol. 6 No.3, pp.72-101.DOI: 10.17705/1jais.00065
- Jianling W., Ziwei Z. & James C., (2020). User Recommendation in Content Curation Platforms. Department of Computer Science and Engineering, Texas A&M University, DOI: 10.1145/3336191.3371822
- Jingjing Zhang & Shawn P. Curley (2018) Exploring Explanation Effects on Consumers' Trust in Online Recommender Agents, International Journal of

Human–Computer Interaction, 34:5, 421-432, DOI: 10.1080/10447318.2017.1357904
- Johansen, I. K., & Guldvik, C. S. (2017). Influencer marketing and purchase intentions: how does influencer marketing affect purchase intentions?
- John O'D & John D. (2004), A Framework for Evaluation of Information Filtering Techniques in an Adaptive Recommender System, Computational Linguistics and Intelligent Text Processing, 5th International Conference, CICLing 2004, Seoul, Korea, February 15-21. DOI: 10.1007/978-3-540-24630-5_62
- Karen, F., Kristin, G., Karen, M., Laura, A. F., (2010). Who are the social media influencers? A study of public perceptions of personality. Public Relations Review, Vol. 37, Issue 1, pp. 90-92. DOI: https://doi.org/10.1016/j.pubrev.2010.11.001
- Kabiawu, O., van Belle, J. P., & Adeyeye, M. (2016). Designing a Knowledge Resource to Address Bounded Rationality and Satisficing for ICT Decisions in Small Organizations. The Electronic Journal of Information Systems in Developing Countries, 73(1), 1-18.
- Keng CJ, Liao TH (2009) Consequences of post purchase dissonance: The mediating role of an external information search. Soc Behav Personality: Int J 37(10):1327–1340
- Kharel, B. (2018). Factors Influencing Online Brand Trust: Evidence from Online Buyers in Kathmandu Valley, 3(1), 47–64.
- Komiak, S., & Benbasat, I. (2006). The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents. Mis Quarterly, 30, 941-960. doi: 10.2307/25148760
- Kunkel, J., Donkers, T., Barbu, C., & Ziegler, J. (2018). Trust-Related Effects of Expertise and Similarity Cues in Human-Generated Recommendations. In HUMANIZE '18: Proceedings of the 2nd Workshop on Theory-Informed User Modeling for Tailoring and Personalizing InterfacesAt. Tokyo. Retrieved 11 December 2020, from https://www.researchgate.net/publication/325106287_Trusthttps://www.researchgate.net/publication/325106287_Trust-Related_Effects_of_Expertise_and_Similarity_Cues_in_Human-Generated_RecommendationsRelated_Effects_of_Expertise_and_Similarity_Cues_in_Humanhttps://www.researchgate.net/publication/325106287_Trust-Related_Effects_of_Expertise_and_Similarity_Cues_in_Human-Generated_RecommendationsGenerated_Recommendations.
- Liao T-H (2017) Online shopping post-payment dissonance: dissonance reduction strategy using online consumer social experiences. Int J Inf Manag 37(6):520–538

- Li, Z., Xiong, F., Wang, X., Chen, H., & Xiong, X. (2019). Topological Influence-Aware Recommendation on Social Networks. Complexity, 2019, 6325654. doi: 10.1155/2019/6325654
- Lowrey T (1998) The effects of syntactic complexity on advertising persuasiveness. Journal of Consumer Psychology 7(2): 187–206.
- Matthias S., Martin G. K., (2006). Trust and trustworthiness across different age groups, Games and Economic Behavior Elsevier, vol. 59(2), pages 364-382. DOI:10.1016/j.geb.2006.07.006
- McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: a trust building model. The journal of strategic information systems, 11(3-4), 297-323.
- Mohammadi, V., Rahmani, A. M., Darwesh, A. M., & Sahafi, A. (2019). Trust-based recommendation systems in Internet of Things: a systematic literature review. Human-centric Computing and Information Sciences, 9(1), 21. doi: 10.1186/s13673-019-0183-8
- Monsuwé, T. P., Dellaert, B. G., & De Ruyter, K. (2004). What drives consumers to shop online? A literature review. International journal of service industry management.
- Newman, D., 2016. Love It Or Hate It: Influencer Marketing Works. Forbes. Available at: https://www.forbes.com/sites/danielnewman/2015/06/23/love-it-or-hate-it-influencerhttps://www.forbes.com/sites/danielnewman/2015/06/23/love-it-or-hate-it-influencer-marketing-works/ - 69bf6392150bmarketing-works/#69bf6392150b
- O'Donovan, J., & Smyth, B. (2005). Trust in recommender systems. International conference on Intelligent user interfaces. pp. 167–174. DOI: https://doi.org/10.1145/1040830.1040870 Pavlou, P. (2003). Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model. International Journal of Electronic Commerce, 7, 101-134.
- Pedro S., Francisco, M., Carolina L., Ricardo, C.(2014), "The effect of information overload and disorganisation on intention to purchase online" The role of perceived risk and internet experience. Online Information Review Vol. 38 No. 4, pp. 543-561. DOI: 10.1108/OIR-01- 2014-0008
- Qiu, L., & Benbasat, I. (2009). Evaluating Anthropomorphic Product Recommendation Agents: A Social Relationship Perspective to Designing Information Systems. Journal of Management Information Systems, 25(4), 145–182. doi:10.2753/mis0742-
- Schwab, D.P., 1980. Construct validity in Organizational behavior. In: Staw, B.M., Cummings, L.L.(Eds.), Research in Organizational Behavior, vol. 2. JAI

Press, Greenwich, CN, pp. 3–43.
- Sheng, X. (2012). Consumer participation and the trust transference process in using online recommendation agents. Journal of Consumer Satisfaction, Dissatisfaction & Complaining Behavior, 25, 96-117.
- Sheppard B and Sherman D (1998) The grammars of trust: A model and general implications. Academy of Management Review 23(3): 422–437
- Sherrie Y. X. K. & Izak B., (2006). The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents. MIS Quarterly, Vol. 30, No. 4 (Dec., 2006), pp. 941-960. DOI: 10.2307/25148760 https://www-jstorhttps://www-jstor-org.ezproxy.ub.unimaas.nl/stable/25148760org.ezproxy.ub.unimaas.nl/stable/25148760
- Shambour, Q., & Lu, J. (2015). An effective recommender system by unifying user and item trust information for B2B applications. Journal of Computer and System Sciences, 81(7), 1110–1126. doi: 10.1016/j.jcss.2014.12.029
- Sidharth M. & Linjuan R. M, (2015). How Peer Communication and Engagement Motivations Influence Social Media Shopping Behavior: Evidence from China and the United States. Cyberpsychology, Behavior, and Social Networking Vol. 18, No. 10. DOI: https://doi.org/10.1089/cyber.2015.0190
- Spreitzer, G. M. (1995). Psychological empowerment in the workplace: Dimensions, measurement and validation. Academy of Management Journal, 38 (5), 1442-1465.
- Sylvain, S. & Jacques, N., (2004).The influence of online product recommendations on consumers' online choices. Journal of Retailing, 80 (2004), pp. 159–169 http://seshttp://ses-perso.telecom-paristech.fr/survey/CanauxInformBienExpe/senecalnantel.pdfperso.telecom-paristech.fr/survey/CanauxInformBienExpe/senecalnantel.pdf
- Tatiana, M., Wesley V. da. S., Adriano M. S., Claudineia K. F. & Claudimar P. da V., (2020). Online customer behavior: perceptions regarding the types of risks incurred through online purchases. Palgrave Communications volume 6, Article number: 13 (2020).
- Vorm, E., & Miller, A. (2020). Assessing the Value of Transparency in Recommender Systems: An End-User Perspective. In roceedings of the 5th Joint Workshop on Interfaces and Human Decision Making for Recommender Systems at ACM Conference on Recommender Systems (RecSys 2018). Vancouver. Retrieved 11 December 2020, from https://www.researchgate.net/publication/328134005_Assessing_the_Value_of_Transparency _in_Recommender_Systems_An_End-User_Perspective.

- Wang, J., Zhu, Z., & Caverlee, J. (2020). User Recommendation in Content Curation Platforms. In WSDM '20: The Thirteenth ACM International Conference on Web Search and Data Mining. Houston. Retrieved 11 December 2020, from http://people.tamu.edu/~jwang713/pubs/curator-wsdm2020.pdf.
- Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: use, characteristics, and impact. Mis Quarterly, 31(1), 137-209.
- Yi, Y., & Gong, T. (2008). The electronic service quality model: The moderating effect of customer self-efficacy. Psychology & Marketing, 25, 587– 601.
- Yuanchun J., Jennifer S., Yezheng L., (2010). Maximizing customer satisfaction through an online recommendation system: A novel associative classification model, Decision Support Systems, Volume 48, Issue 3, Pages 470-479, DOI: https://doi.org/10.1016/j.dss.2009.06.006.
- Yuanping, Y., Fred, F. & Michel, W., (2006). Leveraging Missing Ratings to Improve Online Recommendation Systems. Journal of Marketing Research, Vol. 43, No. 3 (Aug., 2006), pp. 355-365. https://www.jstor.org/stable/30162410
- Yuan, J., & Li, L. (2014). Recommendation Based on Trust Diffusion Model. The Scientific World Journal, 2014, 1–11. doi:10.1155/2014/159594

10. Official Statement of Original Thesis

By signing this statement, I hereby acknowledge the submitted thesis (here after mentioned as “product”), titled: **Trust issues automatic recommendation systems** to be produced independently by me, without external help.
Wherever I paraphrase or cite literally, a reference to the original source (journal, book, report, internet, etc.) is given.
By signing this statement, I explicitly declare that I am aware of the fraud sanctions as stated in the Education and Examination Regulations (EERs) of the SBE.

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