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PEOPLE YOU MAY IGNORE:
users’ perceptions about social matching systems on social network sites

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ABSTRACT

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As the amount of information on the web grows exponentially every year, users rely more and more on recommender systems to find relevant content. On social network sites, recommender systems help users access not only relevant content, but also to connect to people of interest. Due to their central role in social network sites, people-to-people recommender systems have recently gained more attention among the academic community, especially in regards to reciprocity, privacy and their efficiency.

This research aims to understand how people-to-people recommender systems may influence the establishment of new relationships outside and within social media. Therefore, eight social media users were interviewed with a semi-structured questionnaire about their experiences with recommender systems on different social media, such as Facebook, Twitter, Instagram and LinkedIn. All the interviewed users have been using social media for approximately 10 years.

The interviews showed that the relevance of people-to-people recommender systems changes progressively, as users spend more time on social network sites. Considering the profile of the interviewed users and their long exposure to social media, most affirmed to ignore people-to-people recommender systems while browsing throughout social network sites. However, it was possible to conclude that the use of recommender systems in early stages had influenced how they perceive social network sites and how they relate to unknown users in virtual communities.

As a result, this research presents an urgent need and suggestions to improve the design of people-to-people recommender systems, considering the different stages of use of social network sites. A special attention is recommended towards special user groups, such as children, and cultural differences.

Key words: social network sites, recommender systems, social matching systems, online behavior.

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

Contents

1. Introduction

As the world population continually surpasses 7 billion people, our society has to deal with another exponential growth: the data continuously generated by all its population. Taking in consideration the amount of information currently available worldwide, both on and offline, it is essential for web users to have access to tools that automatize and support the filtering of relevant information. With this purpose in mind, recommender systems were developed to support users through navigation in websites and databases. Recommender systems are already widely utilized in e-commerces, streaming platforms and social media, to mention some of its main uses. Based on an understanding of the profile of the user, these mechanisms are capable to predict and suggest the most relevant content to an individual.

Considering the omnipresence and importance of such systems in our society, several studies have been carried out regarding recommender systems [Leino, 2014]. However, most part of these studies seem to focus on either the improvement of such systems, from technical and algorithmic points-of-view, or the commercial impact carried by the implementation of recommender systems in business strategies. Meanwhile, the social impact caused by these mechanisms on users still requires further research, especially regarding how the use of recommender systems in social media may impact the establishment of new interpersonal relationships.

This research aims to investigate and understand the effects that social recommender systems, such as the feature “People you may know” on Facebook, may have on the establishment of new relationships. Considering differences among distinct social networks, the present research also aims to compare the perceptions of genuine users regarding connection suggestions among different social medias. Therefore, this study explored how the suggestions of connections offered by Facebook, Instagram, Twitter and LinkedIn are perceived by its users.

The idea to research this topic originated from two hypothesis regarding alternative uses of people-to-people recommender systems in social network sites. The first hypothesis considered the possibility that SNSs users could gather personal information of people recommended through people-to-people recommender systems, affecting their social skills in face-to-face circumstances. Furthermore, the second hypothesis considered that people-to-people recommender systems could be used as a dating tool, even in cases that they are not meant to be.

2. Interpersonal relationships on the web

This chapter presents an overview of concepts about social network sites (SNSs) and how relationships are formed from different viewpoints, such as sociology, psychology and technology. In addition, considering the particularities of different SNSs, this chapter also illustrates how recommendations and relationships may vary according to the context of different SNSs and how the goals of SNSs users may change over time.

2.1. Defining Social Network Sites

Social network sites (SNSs) were first developed in the 1990s, based on the combination of online dating services and instant messaging platforms [Hoffmann and Bublitz, 2017]. As a central function, social network sites connect their users to other people of interest [Elisson et al., 2014; Pizzato et. al, 2012; Donath and Boyd, 2004], and work as a virtual reunion point for family members, friends, colleagues and acquaintances. Seeing through another perspective, Terveen and McDonald [2005] state that “a social network is a graph that represents people and relationships between them”.

Other definitions of social network sites also consider the profile of their users as a critical factor on SNSs [Boyd and Ellison, 2007]. The creation and personalization of profiles allows users to express theirselves on the web, by entering personal data, such as name or nicknames, age, school, work and interests, to mention a few, or even customizing the design of their own profile pages with exclusive design elements and self-portraits.

On top of personal information, personal profiles on SNSs may also present a list of friends or connections established by users online. Through these lists, users may “view and traverse their list of connections and those made by others within the system” [Boyd and Ellison, 2007] as a way to expand their own networks. In order to keep their platforms attractive and relevant, social network sites may also “analyze our contacts to help us connect with new friends and get hooked with the site” [Lü et al., 2012] in an automatized way, as discussed in more depth in *Subchapter 3.3* about social matching systems.

Connections in social network sites are directly linked to the basic human need of maintaining interpersonal relationships [Elisson et al., 2014]. Related to online relationship maintenance and dissemination of content on the web, social network sites allow their users to communicate among themselves through direct and indirect ways [Elisson et al., 2014]. In the first case, users may send private or direct messages to friends or group of friends. While indirect communication is established by publishing content on personal profiles in order to keep their networks informed about personal thoughts or changes in their lives. Meanwhile, these users' connections may also post messages and graphical content (e.g., photos, videos and music) to other users' profiles. Regarding indirect communication, Elisson et al. [2014] establish a connection between these public updates and triadic closure process (see Section 3.3.1), as friend of friends may also join the conversation and strengthen ties. Meanwhile, Ortega [2016] establishes a relation between the amount of content hosted in SNSs and activity, as the latest seem to increase according to the amount of multimedia content (e.g., videos, photos and other documents) shared by users of social network sites.

2.2. Interpersonal attraction

There are many different factors that gather users in social network sites and motivate them to develop their own personal and virtual communities. This subchapter explores how interests in common, demographics and users' familiarity can impact the development of interpersonal relationships in social network sites. Even though the line that differentiates a point from another is tenuous, it is important to note that 1) interpersonal attraction is not limited to this three points, and 2) it is necessary to consider the own personality of each user and their own inclination towards these or other points, that may be equally or more relevant when establishing new relationships.

2.2.1. Interests in common

At the same time that social network sites aim to connect users to each other, it is not always possible without sharing common points, experiences or interests [Donath and Boyd, 2004]. The authors mention in their work the focus theory developed by Feld [1981], regarding the importance of common goals in order to develop relationships and groups. According to Feld [1981], two people may increase their chances of developing a connection based on their foci. In other words, the more points in common shared by two people, which includes previous relationships, locations, groups and activities, to mention a few, the bigger are the chances of developing a new relationship. In his own words, “a group’s activities are organized by a particular focus to the extent that two individuals who share that focus are more likely to share joint activities with each other than two individuals who do not have that focus in common” [Feld, 1981].

2.2.2.Demographics

When referring to interpersonal attraction and establishment of relationships, demographics play a comparable role to interests in common and familiarity. Similarly to Feld’s [1981] foci theory, and the argument that people who share similar interests have more chances to develop relationships, demographics concern the context that these users are inserted. In other words, users that share a common background, such as education levels, places of residence and age groups, to mention a few, have more chances to develop relationships.

As seen in Hargittai [2008], demographics also impact how and which social network sites are used by a certain user. In her research conducted with students from different background, Hargittai [2008] presents evidences that factors, such as place of residence and level of education, to mention a few, have a role defining which SNSs a user is more inclined to use. Similarly, a later study conducted by Kim et al. [2011] shows that cultural values (e.g., national values or identity) also play an important role defining the social network sites that are used by a certain group of users.

2.2.3.Familiarity

Users of social network sites have a clear tendency to replicate their offline relationships in their online communities or profiles [Hoffmann and Bublitz, 2017; Boyd and Ellison, 2007]. In practice, there is an understanding that users search primarily for already known people to connect with on social network sites, however they are not limited to this type of connections [Mital and Sarkar, 2011; Correa et al., 2010]. As seen in Amichai-Hamburger and Vinitzky [2010], users also have a tendency to filter who is accepted or not in their virtual networks, as their friend lists may impact the way they are perceived by other users.

> “With online identities being increasingly anchored in offline contexts, the ways in which online communities are negotiated and perceived have changed dramatically in recent years. Users increasingly interact with offline acquaintances, while anonymous online activities seem to be on the decline. Thus, online com-

> munities usually reproduce existing offline communities and are firstly built around previously existing offline connections and only secondly around interests.” [Hoffmann and Bublitz, 2017]

Similarly, studies have shown that Facebook users maintain regular contact only with a limited number of users from their friend lists on Facebook [Ellison et al., 2014; Burke et al., 2010]. These studies reinforce that users are open also to acquaintances on their social network sites, even if the communication on SNSs have a tendency to become indirect (i.e., general profile updates instead of private messages).

2.3. Relationship dimensions

Different social network sites come with different functionalities. Even though one of the main purposes of such websites is to connect people to people, this may happen in different ways. As seen in Ido Guy [In Ricci et al., 2015], relationships on SNSs may depend on different factors, such as the reciprocity of connection, approval, the duration expected for relationships and their nature. This subchapter presents how these different factors may influence the establishment of new connections and how they may impact people-to-people recommender systems.

2.3.1.Reciprocity

Reciprocity regards the need of mutual connection among parties in social network sites. In social media platforms, it is possible to have either symmetric or asymmetric relationships [Ricci et al., 2015]. In the first case, a connection between peers relies on the both parties establishing the same connection, usually expressed by a mutual relationship on social media, such as friendships on Facebook and connections on LinkedIn, but not limited to these, as symmetric relationships can also be perceived on Twitter and Instagram, when two users follow each other. On the other hand, asymmetric connections are one-way relationships. As an example of asymmetric relationship, user A follows user B, who is an online celebrity, and does not follow user A in return.

References to symmetric and asymmetric relationships are not new, nor exclusive to social network sites. Horton and Wohl [1956] developed the concept of para-social relationships referring to connections established between celebrities and their audiences. In such cases, “the interaction, characteristically, is one-sided, nondialectical, controlled by the performer, and not susceptible of mutual development” [Horton and Wohl, 1956].

2.3.2.Approval

The approval dimension concerns the need of confirmation or not to establish a new relationship online [Ricci et al., 2015]. Confirmed relationships requires that at least one user accepts the request sent by another, as seen in friend requests on Facebook or private profiles on Twitter or Instagram. In contrast, non-confirmed relationships do not require any approval to be established. As an example of non-confirmed relations, it is possible to follow open Twitter and Instagram profiles without requiring authorization.

As seen in Boyd and Ellison [2007], different social network sites also employ distinct terms that characterize confirmed and non-confirmed relationships, such as Friends, in the first case, and Fans or Followers in the latest.

> "Most SNSs require bi-directional confirmation for Friendship, but some do not. These one-directional ties are sometimes labeled as ‘‘Fans’’ or ‘‘Followers,’’ but many sites call these Friends as well. The term ‘‘Friends’’ can be misleading, because the connection does not necessarily mean friendship in the everyday vernacular sense, and the reasons people connect are varied.” [Boyd and Ellison, 2007]

2.3.3.Duration

Ido Guy [in Ricci et al., 2015] presents two different types of relationship based on its expected duration: ad-hoc and permanent relationships. Ad-hoc relationships refers to those connections established under special circumstances (e.g., a project work, events or tasks to be done). In such cases, the connection may lose its relevance over time (e.g., when the project is finished). However, permanent relationships are based on stronger relationship ties. Meanwhile, as permanent relationships tend to last longer, the connection on social media is established in a way that both parties maintain their relationship also in virtual communities, as previously seen in Ellison et al. [2014].

2.3.4.Nature of relationship

The nature of relationship is closely related to Ido Guy’s theory [In Ricci et al., 2015] that refers to the impact of “the site’s domain” in the way that users utilize social network sites. To put it differently, every SNS has its own functions and goals, such as establishing personal or professional contacts. As seen in Boyd and Ellison [2007], “some sites are designed with specific ethnic, religious, sexual orientation, political, or other identity-driven categories in mind. There are even SNSs for dogs (Dogster) and cats (Catster), although their owners must manage their profiles”. The different goals of each

SNS affect how users perceive and handle their profiles and connections within different social network sites [Hoffmann and Bublitz, 2017]. According to Ricci et al. [2015], "the goals and characteristics of a connection in these sites [Facebook and LinkedIn] are therefore different, as they would be in SNSs of other domains, such as travel, art, cooking, question and answering, etc."

Related to Feld's [1981] theory, even though people tend to connect with similar parties, it is also natural the separation of relationships that have different foci. In this sense, Ido Guy's [In Ricci et al., 2015] perception about the influence of the site's domain shares similar principles: users of social network sites are socially inclined to distribute their relationships among different SNSs, according to the foci of their relationship and the main goal of each site's domain.

2.4. Relevance and purposes over time

In addition to the different dimensions previously presented, Ido Guy [In Ricci et al., 2015] also suggests that the types of relationships in social network sites change over time. Hence, people-to-people recommender systems in SNSs should improve (or renew) their recommendations according to the different periods that users utilize a certain domain. In this subchapter are presented three different types of people-to-people recommendations and their relevance, according to these different stages of SNSs usage.

2.4.1. Connect

Connecting a user to others is the first step in social network sites. In this phase, users are usually connected to people already known out of SNSs, such as friends, family members or coworkers. In this sense, Guy [2018] also refers to it as *recommendation of familiar people*, as the recommended people are supposedly known by the user already before the recommendations.

Connecting to familiar people also infers that the connection is meant to be symmetric, with both parties engaging to establish a relationship [Guy, 2018]. In addition, Guy [2018] differentiates connections according to the "duration" of the relationship. In ad-hoc relationships, for example, the recommendations should also consider and present the context of a suggestion (i.e., why this person is being suggested). In such circumstances, extra information provided (e.g., events that both users attended) may support users to decide on requesting or not a connection.

The recommendation of familiar people in SNSs also contributes to the building phase of virtual networks [Ricci et al., 2015], as users start developing their friend lists in SNSs by "friending" familiar users. As previously seen in this chapter, connections among familiar peers are the most common type of connections in SNSs, as they work primarily as a virtual meeting point to "real world" connections. In addition, according to Guy [2018], suggestions and successful connections between familiar users may increase the engagement of new users of social network sites.

2.4.2.Follow

Users of social network sites can be also invited to follow people of interest, usually unknown by the users in real life. The people who are suggested to be followed by users are usually celebrities or references in a determined subject, or, as called in Guy [2018], *interesting people*. This type of relationship is usually asymmetric, as the user is not followed back in most of the cases.

In order to suggest interesting people, recommender systems relies mostly on *implicit feedback* to identify possible interests of their users [Guy, 2018]. Such type of data collection is discussed in more depth later in this thesis (see Section 3.1.1).

2.4.3.Get to know

According to Ido Guy [In Ricci et al., 2015], this is the last type of recommendations given by people-to-people recommender systems, given after recommendations of familiar and interesting people. In this phase, users of SNSs start receiving recommendations of unknown people, but with who the user may share common interests.

As seen in literature [Ellison et al., 2014; Mital and Sarkar, 2011; Marwick, 2005], users share strong and weak bounds with different people in social network sites. Strong bounds are mostly established within closer relationships (e.g., family members and close friends), while weaker bounds are those between acquaintances or "friends of friends". *Getting to know people* refers mostly to strengthening weak-bounded relationships. As seen in popular people-to-people recommender systems, such as "People You

May Know" used by Facebook and LinkedIn, the connections that two users share play an important role when such systems suggest new connections.

2.5. Summary

As seen in this chapter, a great number of factors contribute to interpersonal relationships, and it is a fact that both online and offline relations are intrinsically related. Even though social network sites are relatively a recent phenomenon, they have been going through a series of changes, impacting not only their own mechanics, but also how users perceive and behave in these virtual communities. As seen in some studies, users are becoming more inclined to have more realist representations of themselves than in the first SNSs developed. More than that, it seems that social network sites are destined to be a virtual space to gather already known people, rather than a place to connect to strangers and develop new relationships.

3. "People you may know"

This chapter introduces the reader to the main concepts regarding recommender systems. At first, recommender systems are presented in a broader way, considering its usage in different platforms, other than social media, from a technologist point of view, considering different techniques used to process data and present recommendations to users. Later in the chapter are presented studies specifically about the use of recommender systems in social media, especially regarding the suggestion of people, also known as social matching systems, and the added value considering the trust in the information presented by these systems.

3.1. An overview on Recommender Systems

During past decade, the world could observe a dramatic increase in the number of people with access to internet. According to The World Bank [2018], approximately 48% of the world population had access to internet in 2017, representing a growth of 137% within a decade. As a matter of fact, the increasing amount of internet users leads to a growing amount of data available on the web. Consequently, web users may find difficulties to locate desired content among everything else available online, leading them to negative emotions and difficulties during decision making processes [Ricci et al., 2015]. Recommender systems, on the other hand, are tools developed to support users to find the most relevant content in a personalized mode, through filtering out the least relevant content based on users' individual goals [Kembellec et al., 2014; Bellogín et al., 2013].

The origin of modern recommender systems is related to the relevance of word-of-mouth among peers to discover new products [Ricci et al., 2015; Kembellec et al., 2014; Leino, 2014; Resnick and Varian, 1997]. As highlighted by the authors, before the existence of recommender systems in e-commerce, for example, consumers would rely on the opinion of friends and specialists, such as critics sections in newspapers [Ricci et al., 2015]. Therefore, recommender systems aim to automatize what was previously an analogical and time consuming task, facilitating and automizing the search for relevant information, and being an alternative to traditional recommendation research methods, when one must search for people with similar interests in order to get testimonials and recommendations about a subject [Leino, 2014]. Therefore, recommenders systems upgrade the traditional word-of-mouth into a global and virtual space, where users have access to opinions from people all over the world, at the same moment that reduces the time necessary to find relevant products and options about them [Rheingold, 2002].

As observed by Lü et al. [2012] , "the task of recommender systems is to turn data on users and their preferences into predictions of users' possible future likes and interests." Moreover, as presented by Resnick and Varian [1997] and Leino [2014], the use of this data, transformation into suggestions and presentation of recommendations may happen in different ways. First of all, despite of the personal characteristics in recommendations, for instance, they do not always have to be personalized or tailored to every end user. In fact, some recommender systems adopt general annotations to its product, such as tagging, which can be seen by all users. Secondly, the authors write about the use of algorithms, or not, by recommender systems, even though algorithms have a central role automatizing recommendation systems. About the matter, it is stated that more textual types of recommender systems (as users reviews, for example) do not always require an algorithm behind its functioning, while filters, for instance, can use algorithms to categorize and present content. It is important to notice the addendum made by Leino [2014] regarding more recent research made on recommender systems. Those consider recommender systems from "the algorithm aspect, personalization of output" point-of-views, being narrower than the first definitions by Resnick and Varian [1997].

In sum, the definitions of recommender systems can be faced from different perspectives. These can be defined from a technologist point of view that concentrates on technical aspects, such as the algorithm behind recommendations, and ignores explicitly user-made reviews, such as written comments describing the experiences of the user with a product. However, other theories consider recommender systems from a wider perspective, when the outcome of a recommender system is not only a list of recommendations, but it also supports users to choose an item from the list, for example, by showing feedback written by other users. [Leino, 2014].

Regarding the definitions of recommendation systems and the research goals of this thesis, the following sections approach recommender systems from the technologist perspective, considering the fabrication of recommendations as an automatized process with personalized outcomes. In addition, this chapter presents the three most relevant algorithmic approaches regarding the fabrication of recommendations in social matching systems. Even though these approaches present faults and criticism, especially at early stages of implementation (e.g., cold start and database limitations), the following sections aim to present the main concepts and logic behind each approach, rather than to evaluate them.

3.1.1. Collaborative filtering

The collaborative filtering (CF) approach consists in creating and assigning profiles of usage in a determined system based on patterns of user behavior and preferences [Ricci et al., 2015; Kembellec et al., 2014; Bellogín et al., 2013]. These profiles can be designed through the analysis of data gathered, also called "inputs", from users in both explicit and implicit ways.

The data collected through explicit feedback consists in engaging users to actively rate products, such as thumbs-up and down to evaluate a movie in a streaming platform, for example [Ricci et al., 2015]. Additionally, it is also possible to infer preferences and assign profiles from an implicit perspective. As presented by Koren & Bell [in Ricci et al., 2015], implicit feedback can be gathered from a series of different sources, such as browsing, purchase and search histories, or "click-through data and browsing time" [Bellogín et al., 2013].

Even though the use of collaborative filtering is commonly associate to item-to-people recommendations, this approach can be equally utilized in people-to-people recommendations, as seen in Krzywicki et al. [2014] and Cai et al. [2010]. According to the authors, people recommendations generated by a collaborative filtering approach can increase the success rate of profile matching. However, in a social network context, collaborative filtering must consider "the bilateral nature of such interactions in people recommendation" [Cai et al., 2010]. To put in other words, CF systems traditionally only consider the view from the point of view of one active user, while in a SNS context, it must consider the taste of two active users, who are also the object being recommended.

3.1.2. Content-based recommender systems

Different from collaborative filtering, content-based recommender systems (CBRSs), as the name suggests, consider exclusively the characteristics of a product (or its content) and the similarity with other products previously consumed by the user. This type of recommender system relies mostly on metadata associated to an item or the description of this product [Ricci et al., 2015]. Moreover, CBRSs compare characteristics of goods consumed by the user and suggests other items with similar aspects that may be relevant [Krzywicki et al., 2014].

In social media circumstances, people-to-people recommendations may also be perceived from the CBRSs perspective. As seen in Pizzato et al. [2012], "content-based approach assumes that if two people post content on similar topics, they are likely to be pleased to get to know each other". Utilizing the functionality "People You may Know" from Facebook as an example, it is possible to identify common points between the user and the recommended people, other than similar post content. As e-commerces may suggest new books based on genres or authors previously read by the user, Facebook suggests people based on common connections and interests (e.g. hometown, workplace or educational background, to mention a few). However, the use of CBRS approaches in people recommendation may lead recommender systems to suggest unknown people to the active user, while CF algorithms are more efficient to present already known contacts [Pizzato et al., 2012].

3.1.3. Context-aware recommender systems

As seen in Adomavicius et al. [2011] and Ricci et al. [2015], more traditional approaches used in recommender systems, such as collaborative filtering and CBRSs, do not fully consider the context that a recommendation is given, limiting itself to a match between user interests and product characteristics. Context-aware recommenders systems (CARS) supply this gap by considering other factors, "such as time, place, and the company of other people" [Ricci et al., 2015].

Adomavicius et al. [2011] present four different types of contextual information to be considered in CARS: physical, social, interaction media and modal context. Physical context reunites information about the conditions that an active is situated, such as time, weather and location. Meanwhile, the social context adds other people to the equation, identifying their roles and proximity with the active user (as if the user belongs a group or not while using the application). The third context, interaction media, regards the device being handled by the user, such as a mobile phone or tablet, and the type of media that is browsed (e.g., text or multimedia content). Finally, the mood context comprehends “the current state of mind of the user, the user’s goals, mood, experience, and cognitive capabilities” [Adomavicius et al., 2011]. However, the contexts in recommender systems are not in any way limited to these four points, as observed by Adomavicius et al. [2011].

In conclusion, it is possible to identify several different sources of data, combined by recommender systems in order to provide more accurate and relevant informations to end users. Additionally, it is important to notice the central role of the users, participating actively, or not, to generate information.

3.2. User experience of recommender systems

According to Leino [2014], recommender systems have a double impact on systems, both to end users and the companies developing the softwares. In one hand, the companies behind the recommender systems development are benefited by better sales or usage of its system by their end users, becoming more relevant to their own clients and, consequently, improving their own profits. On the other hand, users are benefited by confidence about the information being presented, increasing their trust during the decision making process. [Leino, 2014].

As seen in Krzywicki et al. [2014], recommender systems may impact users in different ways, such as by improving the general user experience within a system, and supporting users when in contact with a large amount of information. Similarly, Jameson et al. [In Ricci et al., 2015] suggest that the main purpose of recommender systems is to support its users to be satisfied with their choices (even in cases when the recommendations given by a system are ignored by the user). By understanding its user’s profiles, recommender systems may evaluate and predict what type of content is relevant or not to each user [Lü et al., 2012], based on its own profile and the data collected from other users with similar behavioral and demographic profiles.

When it comes to recommender systems, studies have shown that users are willing to provide personal information in order to receive better and more accurate recommendations [Ricci et al., 2015; Pizzato et al., 2012]. However, it is important to notice that this relationship with data is not took for granted by other researchers, that highlight some limitations when it comes to privacy and access to sensitive information [Knijnenburg and Kobsa, 2013; Konstan and Riedl, 2012]. Additionally, Knijnenburg et al. [2012] consider privacy control as a factor that counts towards the user experience in recommender systems.

To summarize, user experience in recommender systems can be perceived from different point of views, other than just the algorithm behind them. First of all, to ensure a great user experience, it is fundamental that RS support their users to make the best choice. Even though this aspect is closely related to the algorithm and the capability of prediction of recommender systems, it is also fundamental to consider ways of making users comfortable while using RS. In this sense, recommender systems should also encourage trust among their users, in the sense that users will feel comfortable to share their data and also trust the recommendations. Because trust plays an important role in recommender systems, the next section explores how trust is perceived in RS.

3.2.1. The Trust Factor

As seen in literature, the concept of trust itself is not consensual among different theories. In this thesis, trust is considered from Grandison and Sloman's [2000] point of view.

> "Trust is usually specified in terms of a relationship between a trustor, the subject that trusts a target entity, and a trustee (i.e., the entity that is trusted). Trust forms the basis for allowing a trustee to use or manipulate resources owned by a trustor or may influence a trustor's decision to use a service provided by a trustee." [Grandison and Sloman, 2000].

Applying to the reality in recommender systems, trust is how influential a system can be in a way that motivates its users to consume what was suggested by it.

Abdul-Rahman and Hailes [1997] stated that trust "is subjective, and there will always be hidden factors (intentional or subconsciously) behind a decision to trust or distrust". Later in their work [Abdul-Rahman and Hailes, 2000], the authors also present three different types of trust: interpersonal trust, system or impersonal trust, and dispositional trust. In the first case, trust is relative to an agent and a context (i.e., it may change according to the executioner and the task); second, system or impersonal trust disregards the trustee (i.e., the person who is trusted), relying, as the name suggests, on a system, such as monetary system [Abdul-Rahman and Hailes, 2000]; third, dispositional trust regard the inherent trust that every person has regarding the world, or, as appointed by the authors, it is a "basic trust" that "describes the general trusting attitude of the truster" [Abdul-Rahman and Hailes, 2000].

Regarding recommender systems, it is perceive on literature that transparency in RS is crucial for the establishment of trust between user and platform. Once the active user has access to the reasoning behind a recommendation (i.e., why something was recommended), it is possible for the user to re-state (and confirm) if a recommendation is relevant or not. According to Pizzato et al. [2012],

> "The transparency of a recommender, or the degree to which the user can understand why a particular recommendation is made, has been shown to be an important feature of recommender systems. It gives users a sense of security, confidence and trust in the system." [Pizzato et al., 2012]

However, it is importance to note that Pizzato et al. [2012] also appoint limitations regarding the transparency of recommender systems, such as in reciprocal recommenders. In such cases, it could present sensitive information (e.g., user A is being recommended to you because he or she likes user B) that could also lead users to bad experiences within the system.

In addition to trust, literature in recommender systems also mention about credibility and reputation. As seen in Fogg et al. [2013], when evaluating websites, users consider design aspects of webpages as the main element aggregating credibility to it. From this perspective, it is possible to infer that trust factors may not be exclusive to the recommendations generated, but also the format that information is presented. Moreover, Guy [In Ricci et al., 2015] adds to the discussion the concept of reputation when referring to social recommender systems. In his words, "reputation represents a more general concept about a person's perception by others" [Ricci et al., 2015], with similar understanding to the concept of interpersonal trust stated by Abdul-Rahman and Hailes [1997].

Gunawardana and Shani [In Ricci et al., 2015] suggest that, in order to improve the trust of users in a recommender systems, the latest should recommend also objects already known and liked by the users. Even though the users are less willingly to consume the same product again, they may develop trust regarding the judgment of the system about their own preferences. As an illustration, imagine a group of users that starts listening to music in a new streaming platform. By suggesting music already known and liked by these users, it is likely that they would believe that the streaming platform is aware of their musical taste, and therefore this system should also be able to suggest new songs that would match that taste.

As can be seen, trust is an elastic concept when related to recommender systems. However, it is undeniable how important is trust when considering decision making processes and the success of recommender systems [Grandison and Sloman, 2000].

3.3. Social Matching Systems

As presented by Terveen and McDonald [2005], social matching systems (SMSs) are responsible to connect people with common interests or objectives in an automatized way. At the same time that recommender systems can be considered a technological version of word-of-mouth, social matching systems can be described as ways to "(partially) automate the process of bringing people together" [Terveen and McDonald, 2005].

The authors differentiate social matching systems from recommender systems by the object of recommendation. In this case, social matching systems recommends other users' profiles to establish a connection with, while the latest focus on the recommendation of products or content to be consumed by users [Terveen and McDonald, 2005].

Social matching systems can be used in a series of different applications. As studied by Guy [in Ricci et al., 2015], SMSs may improve the connectivity of colleagues within an working place, or be used to improve matches in online dating sites, as seen in Krzywicki et al. [2014]. In this thesis, social matching systems are studied from a social network sites perspective, where peers are recommended as potential connections to a user, understanding different contexts and goals of each SNS.

As noticed in several studies, it is important that social matching systems consider the interests of both parties in order to establish a successful connection, i.e., when both parties have mutual interest in establishing a relationship [Krzywicki et al., 2014;

Cai et al., 2010; Kim et al., 2010; Pizzato et al., 2012]. Pizzato et al. [2011; 2012] refers to people-to-people matching as *reciprocal recommender*, due to its role "establishing reciprocal relationships between people in domains such as in online dating sites, employment websites (which aim to match employees and employers), mentor-mentee matching and matching helper and helpees". According to the authors, the non-reciprocity in social matching systems may lead users to negative experiences, such as the feeling of frustration and rejection. Moreover, when comparing reciprocal recommendations to traditional item-to-people recommendations (e.g., e-commerce and streaming platforms), it is possible to perceive that the cost of providing bad recommendations in SMS is much higher than in the latest.

> "[…] consider a scenario where a user, Bob, is recommended to another user, Alice; this recommendation is only successful if both Alice and Bob reciprocally agree that the recommendation is good. Importantly, the interaction is staged. At the first stage, it is like other recommenders in the fact that Alice is presented with a set of recommendations and she can simply ignore the one for Bob if she does not like that recommendation (Bob may never know that he was recommended). However, it can be highly costly to the system if Alice initiates a contact with Bob and he then rejects her. If the same situation happens repeatedly, it may cause Alice to feel the anguish of repeated rejection." [Pizzato et al., 2011]

In addition to reciprocity, the volume of people being recommended in social matching systems must also be considered, as a large amount of recommendations may lead users to negative experiences within the system. With a larger number of recommendations, a SMS may also increase the chances of rejection of its users. On the other hand, a limited and reduced amount of recommendations allows users to analyze profiles with more depth and select the most relevant ones to establish contact.

> "[…] it is critical to avoid giving candidates who are likely to reject a user's contact. A people-to-people recommender system must therefore take into account a user's taste (the people they find desirable) but also their attractiveness (how likely they are to be accepted by a potential candidate), since both of these factors determine the success of an interaction. Another important difference is that, while the same item can be recommended to a large number of users (since an item can be repeatedly reproduced), people can accept only a limited number of contacts. So a people-to-people recommender system should not suggest the same candidate to too many users at the same time." [Krzywicki et al., 2014].

3.3.1. Triadic closure process

When it comes to relationships, a triad represents a group of three people. According to Hong et al. [2015], it is possible to differentiate these groups in open and close triads. A closed triad takes place when all the three members of the group have a relationship with each other, while in an open triad two members of the group do not know each other, even though they are connected by a friend in common [Hong et al., 2015].

Triadic closure process takes place when an open triad evolves into a closed one. To put in other words, a triadic closure process happens when two members of a triad, that do not know each other, also develop a relationship among them. This discussion was initiated by Granovetter [1973], who stated that two people, who share weak ties among them and strong ties with a third person, may develop a stronger relationship. This is given due to similarities that the people of certain groups may share.

As seen in Hong et al. [2015], there are several studies proving the high probabilities of developing relationships based in friends in common. As an example, Lou et al. [2013] showed that a user on Twitter has more chances of receiving follow back from accounts that share follows in common. To illustrate, imagine that user A follows and is followed by user B; user A then follows user C, who also follows and is followed by B. In this scenario, according to Lou et al. [2013], there are higher chances of user A being followed reciprocally by user C.

With this in mind, it is important to understand the role that triadic closure process has in both social matching and social recommender systems, since relationships in common are one of the most common factors in people-to-people recommendations. As seen in Terveen and McDonald [2005], "individuals with similar personal characteristics are likely to be attracted to each other. In the language of recommender systems, personal characteristics function as tastes or preferences that one individual may have about another." From another perspective, it is possible to infer from the literature that social matching systems, up to a certain extension, may automatize the process of triadic closure by often recommending friends of friends as potential connections.

3.4. Summary

As presented in this chapter, the increasing popularity of recommender systems follows the trending dissemination of access to internet across the world. In addition to users, more gadgets are also connecting to the internet, elevating the generation of data to higher levels . Recommender systems support users to deal with all the information by filtering the most relevant ones based on user’s behavior. Such systems are also applied to the reality of social network systems, recommending both content to be consumed, as people to who users may be interested in establishing a connection with.

Concerning people-to-people recommendations, research about this topic is usually conducted from a technical perspective, considering the accuracy and functionality of tested algorithms. Such studies, despite of its importance for the development of more accurate and reliable systems, have their focus upon adoption, rather than on user factors, such as user experiences and behavioral implications. In addition, studies related to people-to-people recommendations (or social matching systems) are usually conducted in a controlled environment, or limited SNSs, such as sites created by companies for team building. These studies are also unable to fully comprehend how users' behaviors may change over time, as most of them are limited to short windows of research time.

As explored in the following chapters, this study aims to have a broader glance on people-to-people recommender systems in real settings. To put in other words, this research explores how social matching systems are used in context of broadly known social network sites, such as Facebook, Twitter and LinkedIn, and how users perceive such tools.

4. Social-psychological foundations of behavior in SNSs

Several studies have established a direct relationship between the use of social network sites and behavioral changes in users. While people-to-people recommender systems promote new connections in SNSs, users of these sites may become more susceptible to negative experiences as their social networks are expanded. This chapter introduces the reader to some of the main psychological and behavioral implications related to the use of SNSs. First, this chapter presents how the exposure to social network sites may lead users to depression, considering the way that users utilize SNSs to re-create improved versions of themselves, how these profiles are perceived by other users and how users compared their own lives with the lives presented online. Later, another topic presented in this chapter is online bullying and harassment.

4.1. Adverse effects of social connectedness

Even though most social network sites enable the creation and customization of user profiles intending that users will reproduce their truly selves, researches have shown that this is not always what happens [Boyd and Ellison, 2007; Marwick, 2005]. In reality, studies have presented evidences that users often create better versions of their own realities, or have carefully selected the content to be shared, as a form to create a perfect virtual life. According to Boyd [in Boyd and Ellison, 2007], users' virtual profiles can never be considered entirely real, owing to the fact that it cannot fully replicate the reality of the user behind it. Considering the differences between reality and representations of reality in social network sites, this subchapter approaches how misrepresentations of self are given in SNSs, and how this behavior may impact not only users, but the entire community involved in social network sites.

4.1.1. The benefits of Social Capital and risks of low self-esteem

Studies correlating the use of social network sites and psychological consequences, such as depression, seems to be inconclusive, as noticed by Steinfield et al. [2008]. On the other hand, there is apparently a clear distinction between the use of SNSs by users with low and high self-esteems, considering self-esteem as confidence towards other people and satisfaction with self [Steinfield et al., 2008]. Considering that low self-esteem users "might face more difficulties than high self-esteem individuals in approaching people in their classes or their dormitories, and hence might not form the casual relationships so essential to bridging social capital" [Steinfield et al., 2008], social network sites enable this type of user to connect and develop social ties. More than that, Attrill and Jalil [2011] identified a sense of safety relate to online communication. According to the authors, "the fear of social rejection or non-acceptance from one's nearest and dearest may thus not be prevalent when communicating with potential friends or lovers online" [Attrill and Jalil, 2011].

As seen in several studies [Ellison et al., 2014; Manago et al., 2012; Burke et al., 2010; Steinfield et al., 2008; Donath and Boyd, 2004], the use of social network sites allow users to expand their social capital, or, in other words, SNSs allow users to develop new relationships and strengthen social ties with friends and friends of friends, also benefiting from these relationships somehow. Steinfield et al. [2008] defines social capital as the benefit that one gets from social relationships (such as belongingness to a group), also related to well-being and healthy behavior.

Different studies carried over the past years have also shown that the average number of connections that students posses on Facebook is increasing [Manago et al., 2012]. This fact contributes to the understanding of types of connections established by users on social network sites and how it changed over the years. However, it is fundamental to add that, at the same time, more people started having access to internet (as seen in *Chapter 3*) and, consequently, to social network sites in the past years, contributing to and the increasing average number of friends. As seen in Manago et al. [2012], it is usual that great part of users' friend lists on SNSs are composed mostly by acquaintances (notice that it does not refer to unknown people), at the same time that well-known people are the minority among all the connections. These changes in number of friends can also be related to a desire of expanding social capital, and consequently benefiting from these social relationships.

Additionally to connecting with friends, the use of social network sites is also intrinsically related to a personal seek for social and emotional supports. Social network sites provide a place where users can connect to friends and loved ones in a convenient way, allowing quick communication and the possibility of sharing life events to a large audience [Krasnova et al., 2013; Kim et al., 2011]. Factors, such as self-esteem and the need of social capital, can also shape the way that users behave on social network sites.

One of the effects include the way that they present theirselves and their realities on SNSs. The next section expands the discussion on the causes and effects related to discrepancies between online and offline personalities.

4.1.2.Distorted representation of reality in SNSs

In social network sites, the self-representation of users in their personal profiles may vary in accuracy when compared to the reality. In the words of Amichai-Hamburger and Vinitzky [2010], "people on Facebook and other social networks do not so much as lie, but rather stretch the truth (sometimes to its outer limits)", as to say that users have a tendency to distort real events in a social network reality. In addition, users of social network sites have more control over the information shared online, than they would have in face-to-face situations. According to Ong et al. [2011], the control over information allows SNSs users to create self-representations in a strategic way (i.e., selecting the information that will be shared online in a way that supports the establishment of a desired image of themselves). In similar way, Attrill and Jalil [2011] observed that users also have control over conversations established in virtual circumstances. This control allows users to reflect and ponder about the subjects of conversation, as there is no strict need to answer instantly, contrary to what would be the case in face-to-face conversational situations.

The process of disseminating personal information, especially related to the reality of social network sites, is called self-disclosure. According to Contena et al. [2015], self-disclosure is given in three different dimensions: 1) reciprocity, meaning that people disclosure information motivated by the desire of others sharing information in return (also seen in Attrill and Jalil, 2011]; 2) breadth, referring to the duration or frequency that personal information is disclosed to others; and 3) depth, related to how intimate, or private, the information disclosed is. At this point, it is importance to notice the relevance of self-disclosure in social network sites, as SNSs rely mostly on users willingly to share personal information, in order to establish interactions among them. More than that, Attrill and Jalil [2011] observed that self-disclosure tends to occur more rapidly in virtual situations, such as in social network sites, than in communication situations without computer mediation.

The difference in how self-disclosure happens in real and online worlds may be related to the explanation given by Donath and Boyd [2004]. According to the authors, while a person is attached to a physical body in real world, changes of identity are not as possible as in virtual circumstances, when users are free to re-create profiles when necessary, being also able to re-build a completely new identity, starting by online user-names.

> "Identity deception is prevalent in the on-line world. In the real world the body anchors identity, making it both singular and difficult to change. Identity deception, though not unheard of, is difficult — convincingly representing oneself as a member of the opposite gender is quite costly, requiring extensive makeup, costuming, and possibly surgery, while portraying oneself as a different person requires acquiring another's documents, avoiding known acquaintances, and risking a lengthy incarceration. On-line, identity is mutable and unanchored by the body that is its locus in the real world. In many situations, creating pseudonyms has little cost and if one ruins the on-line reputation tied to one screen name, it is simple to acquire a new name and return afresh. Behind the new name is the same problematic person, but the equivalence between the disreputable old name and the clean new name — the fact that they are both names for the same person — is invisible." [Donath and Boyd, 2004]

Similarly, as seen in Mehdizadeh [2010], social network sites, such as Facebook, allow users to express a "hoped-for possible self", a type of "possible-self" described by the author as an identity unknown by others. In other words, the possible-self is a somehow incomplete identity, expressed in selected portions, while unwanted characteristics of self remain in secret.

These modifications, or filters of reality, in online identities allow users of social network medias to expose a stretched reality, as earlier mentioned in this section and appointed by Amichai-Hamburger and Vinitzky [2010]. Moreover, different researches have present a comparison of different psychological effects, both positive and negative, depending on how social network sites are used. On one hand, users seem to elevate their self-esteem by updating their own profiles. On the other hand, however, when users become spectators on SNSs (such as while browsing other users' profiles), users tend to experience negative emotions [Lup et al., 2015; Krasnova et al., 2013; Gonzales and Hancock, 2011].

> "Passively looking at others' profiles displaying photos of vacations or social events to which one was not invited often triggers resentment, envy, and loneliness. Jealousy and relationship problems can result from spending too much time on profiles of romantic partners, and contact with ex-partners prevents people from post-breakup healing. In adolescent girls, emotional investment in social networking has been linked to lower self-esteem and depressed mood, and exposure to SNS that emphasize appearance has been linked to increased body image disturbance." [Lup et al., 2015]

As presented in the next section, these alternative narratives, created by users exclusively for their profiles on social network sites, can also affect how other users perceive theirs eves and their own realities.

4.1.3.Social comparison theory

As presented by Lee [2014], people have a natural tendency to compare themselves with other parties, as more knowledge about each other is acquired. This phenomenon is called social comparison and may vary depending on different factors, such as self-esteem and object of comparison. Additionally, some researches [see Lee, 2004] have shown that social comparison is often stronger on younger people, such as students, as the comparison itself contributes towards the development of one's psyche and identity, and tends to decrease its intensity over time. Meanwhile, in a research about users' motivation towards social network sites, Kim et al. [2011] identified a common trend among students from United States and South Korea: in both contexts, students' main motivation while using SNSs was to search for friends and establish new connections, in similar manner as meeting new people.

Social network sites, that are widely used by adolescents, supports young users in the social comparison process, as "these sites present platforms to connect to their peers without adult surveillance and to facilitate identity construction and experimentation within a social context" [Ong et al., 2011]. Additionally, studies have shown that, specially when connecting to strangers through social network sites, users have more tendency to experience negative emotions. In such cases, users tend to compare their own lives with the updates shared by unknown people in real life, questioning their own lives and experiences in a negative way [Lup et al., 2015]. These series of negative emotions originated from online social comparison may lead users to reduce or avoid contact with social network sites, a clear negative outcome for the providers of such services [Krasnova et al., 2013].

In a study conducted by Krasnova et al. [2013], Facebook users shared their experiences, emotions and perspectives related to the use of the SNS. When questioned about the negatives feelings experienced by other users, the respondents believed that envy would be the biggest reason of frustration of users on Facebook (29,6%), followed by lack of attention (19,5%). Regarding the main causes of envy on Facebook, the main reasons would be published content related to travel and leisure (56,3%) and social interaction (14,1%).

At this point, it is necessary to understand that envy, as analyzed by Tandoc Jr. et al. [2015], refers to desiring something that one does not have access to, but is owned by others. Additionally, envy may lead one to perform "volatile and hostile actions toward the target of envy" [Tandoc Jr. et al., 2015]. Lin and Utz [2015], however, categorize envy in two types: benign and malicious. In their study, the authors compare how different types of envy occur depending on the strength of social ties between the user who posts and the user who reads. As of their research, the results show that users with strong social ties are more likely to experience benign envy, while low evidences show that users are prone to experience malicious envy in weak ties relationships. According to Lin and Utz [2015], the later finding can also be compared to offline settings, as malicious envy is supposedly less usual than benign envy.

Next, considering hostile behavior in the context of SNSs, the following subchapter explores other negative behaviors towards users of social network sites, such as online harassment and cyberbullying.

4.2. Online harassment and cyberbullying

As a matter of fact, users of SNSs are exposed not only to distorted realities and potential decrease of self-esteem (when comparing that their lives are not as perfect as the others seen in SNSs), but also to negative behavior of other users towards them. In some cases, the anonymity factor allows some users to behave in these negative ways, such as online harassment and cyberbullying. People-to-people recommender systems may support connections that could be disclosed as dangerous or unsafe after the connection is established and one user starts behaving inadequately towards the other.

Jones and Mitchell [2016] define online harassment as "threats or other offensive or rude behavior targeted directly to youth through technological channels (e.g., Internet, text messaging) or posted online about victims for others to see". According to this definition and further research, the authors identify a large gap among different studies referring to how often users suffer online harassment. One of the reasons for these discrepancies would be that not everyone, who is online harassed, perceives online misbehavior as harassment [Jones and Mitchell, 2016; Lwina et al., 2012; Wolak et al., 2007]. Similarly, the concepts of cyberbullying in academy also vary across literature, what contributes "to the inconsistency in findings across studies. A lack of consensus complicates cross-study comparisons and, thus, limits research progress” [Ybarra et al., 2012]. However, according to the definition found on Oxford Dictionary, cyberbullying is defined as “the use of electronic communication to bully a person, typically by sending messages of an intimidating or threatening nature” [Oxford University Press, 2018].

Some types of online harassment, as seen in Jones and Mitchell [2016], include being called by mean names, being exclude from virtual groups, being teased or having rumors spread (including dissemination of material, such as photos and videos, with the intention of embarrassment). Regarding cyberbullying, research have shown evidences that, even though these actions are usually performed anonymously, the bully is usually known at a certain level by the one who is bullied [Ybarra et al., 2012; Wolak et al., 2007].

A study conducted by Näsi et al. [2014] comparing online misbehavior in Finland and United States showed that women (specially in Finland) are more likely to suffer online harassment. Similar results are found in Jones and Mitchell [2016]: 69% of online harassment victims in 2010 were expected to be women. Another alarming finding is that most part of victims is composed by children between 13 and 17 years old. Comparatively to what was presented in previous parts of this research, psychological and social skills are developed during this stage of live. In addition, access to some social network sites is already possible at the age of 13. These factors reinforce the impact and responsibility that these sites have regarding users’ mental development, specially regarding young ones.

Even though online harassment cases are not strictly related to social recommender systems *per se*, they may negatively impact user perceptions about connecting to unknown users, and therefore also to users suggested through social recommender systems. For this reason, it is necessary to think about the user experience in social media as a whole. With this in mind, it is important to notice that social recommender systems are just a small fraction from the whole social media environment. What is experienced by the user in other parts of social media (i.e. online harassment from unknown profiles) may impact the way that other tools are used. In other words, bad experiences may decrease trust in the system, and therefore also affect people-to-people recommender systems.

4.3. Summary

This chapter presented how psychological and behavioral factors are connected and affected by the use of social network sites. As previously seen, users' profiles in SNSs are not only a virtual space to express their personalities, but rather a social vitrine, where users can present improved versions of their own realities and personalities (i.e., how they would like to be perceived by others). This behavior in SNSs however has other implications than only self-image. Research has shown that people (including SNSs users) have a tendency to compare theirselves with others, or the image that they have of others and how this image relates to their self-images. In the reality of social network sites, social comparison can lead users to experience negative emotions (such as envy), in addition to the eminent risk of experiencing also online harassment and cyberbullying. All these risks have a serious impact on users' behavior and perception of social network sites, leading them to reduce, or to cease, their presence on SNSs.

5. Methodology

The present thesis aimed to investigate the relationship between people-to-people recommender systems and the development of social relationships among users of social network sites. The research question that guided this research was "how recommender systems in social media platforms (such as "People You May Know" of Facebook) impact the establishment of interpersonal relationships?" Hence this research was built from a qualitative perspective, upon bibliographic review and interviews.

Bibliographic review supported this thesis by presenting theories and concepts regarding recommender systems, social media and the psychological impact that the last has on its users, as presented in the previous chapters.

Meanwhile, as pointed by Buder & Schwind [In Leino, 2014, pp. 5], studies and information regarding interaction between user and recommender systems are limited (i.e., the relation cause and effect in RS). Indeed, understanding user's perspectives is essential in order to comprehend how these systems may impact their attitudes, online and offline. For this reason, user interviews were also conducted in order to compare their own experiences regarding social media and people-to-people recommender systems, and the literature.

5.1. Interviews

For the present thesis, eight social media users were interviewed. The interviewees were regular users of SNSs and also aware of social recommender systems in the social network sites used by them. Regular users (rather than hard users) were selected in order to have genuine and standard perspectives about people-to-people recommender systems.

The length of interviews was 25 minutes on average, being held on places suggested by the own interviewees. The interviews covered different topics about their social lives and social media usage, such as means of communication with family and friends, social relationships, differences in the process of knowing new people online and offline, opinions and thoughts about people recommended through recommender systems, trust and social research (as in searching information online about other people). The semi-structured questionnaire utilized during the interviews, as well as the transcriptions, are available integrally at the end of this thesis as an appendix.

In order to keep the interviewees' anonymity, they will be referred by their profile, such as in gender, age and relationship status, when necessary.

5.1.1. Participants

The eight interviewees can be divided equally in two major groups: four users (being two men and two women) who were single at the moment of the interview, and four users (being two men and two women) who were in any type of relationship or engaged to someone else.

The ages of the interviewees ranged from 25 to 36 years old, with an average of 30 years old. At this age, the interviewees showed maturity and understanding regarding social and affective relationships, in addition to longer exposure to social media and its features. As main activities, most of the interviews (6 out of 8) pointed a professional activity as main occupation, like marketing, engineering, design and information technologies. Two interviewees were full-time students.

Most of the users interviewed utilize regularly Facebook, Instagram and LinkedIn, while some also utilized Twitter and Snapchat, among other more specific cases (such as WeChat, VK, Pinterest and 500px). Important to note that 7 out of 8 interviewees declared "mobile" as the main device to access their social media, while one interviewee appointed "desktop" as the main gadget. About the daily usage of social medias, the interviewees spend at least one hour a day and 6 at most, navigating through social media for more than 3 hours per day in average (see Table 1).

Among the interviewees, messaging tools, such as SMS, WhatsApp and Facebook Messenger, appear to be the main ways to keep in touch with people who are closer affectively, but not necessarily close physically. By messaging, it is possible to keep track in a more personal way, since the message is not meant to the whole audience. Phone and video calls were also mentioned as ways of maintaining contact with closest friends and relatives.

More traditional social media, such as Facebook or Instagram, are considered by the interviewees mostly as a way to share and consume information in a broader way. According to the users interviewed, it is possible to have a panorama of what is happening in the lives of friends by reading the news feed, and also to update their friends about their own lives. As these social medias are updated, users have their messages spread in faster and broader ways than private messaging. On the other hand, LinkedIn was not mentioned as a way to keep in touch with friends, but to have a glimpse of professional updates by colleagues or former co-workers. Because of the ease of following updates from friends, many interviewees suggested that this would be one of the main reasons to continue using social media, in addition to not requiring any commitment or thinking.

#ID	Gender	Age	Relationship status	Nationality	Profession	Used SNSs	Hours per day in SNSs
#1	F	36	Single	Finnish	Graphic Designer	Facebook, Instagram, LinkedIn	2
#2	F	27	Single	Byelorussian	Journalist	Facebook, Twitter, LinkedIn, VK	6
#3	F	31	Married	Greek	Marketing	Facebook, Instagram, LinkedIn, Pinterest	5
#4	F	25	Dating	Chinese	Student	Instagram, LinkedIn, Snapchat, WeChat	2
#5	M	34	Single	Finnish	Student	Facebook, Instagram, LinkedIn, Pinterest	1
#6	M	31	Single	Brazilian	Engineer	Facebook, Instagram, Twitter, LinkedIn, Snapchat, Pinterest	5
#7	M	29	Living together	Finnish	Photographer	Instagram, Twitter, 500px	2
#8	M	27	Dating	Brazilian	Systems specialist	Facebook, Instagram, Twitter, LinkedIn	4

Table 1. Profile of interviewed participants.

5.1.2. Data analysis

As the conducted interviews resulted in qualitative data, they were analyzed by utilizing visualization techniques, such as affinity diagram and mental map. The analysis focused in finding common points among the interviews, rather than user specific particularities, in order to have a broader understanding about the subject. In the next chapter, the main findings of the interviews are presented following the most common points among the users. In addition, is explored how the perspectives on people-to-people recommender systems change according to different social network sites.

6. Findings

The interviews conducted with SNSs users provided different perspectives about the utilization of social network sites and the people-to-people recommender systems utilized by them. This chapter presents the main findings and outcomes from the interviews and a description of their relationship with people-to-people recommendations. First, this chapter illustrates how the relationship between user and recommender systems changes according to the time spent by the users in social network sites. In sequence is discussed the importance of information availability and common interests between users and recommendations from the interviewees perspectives. Later in this chapter is discussed how the perception on people-to-people recommender systems changes among different social network sites and particularities from different cultures and profiles.

6.1. Relevance of recommendations changes over time

Comparing the different experiences that the users interviewed were exposed to while using social network sites, such as Facebook, Twitter, Instagram and LinkedIn, there was one strong and similar phenomenon among them: users experienced a decreasing relevance of people-to-people recommender systems in social network sites used regularly by them. At this point, it is important to re-estate that most users interviewed have been using at least one SNS since school years (usually Facebook), meaning that their relationship with some SNSs had been already established for years at the moment that the interviews were held.

This subchapter presents how the relevance of people-to-people recommender systems changed over time, according to the users. For this purpose, the content of this section is divided about perceptions of new users (*Section 6.1.1.*), referring to users at the moment that they had recently created an account in any SNS; middle experiences (*Section 6.1.2*), exploring how the recommendations impacted their use of SNSs after the initial phases; and ignoring phase (*Section 6.1.3*), describing the current stage that most of the users found themselves at the moment of the interviews.

The different phases, and the changes in level of relevance, can also be visualized below in Picture 1. The graph presented in Picture 1 is not by any means validated statistically, nor is meant to be a generalization of the universe. Rather, it presents common and strong points between the interviews realized for the purpose of this research, as it was created with the intent of illustrating the evolution of the relevance of people-to-people recommender systems in a visual manner.

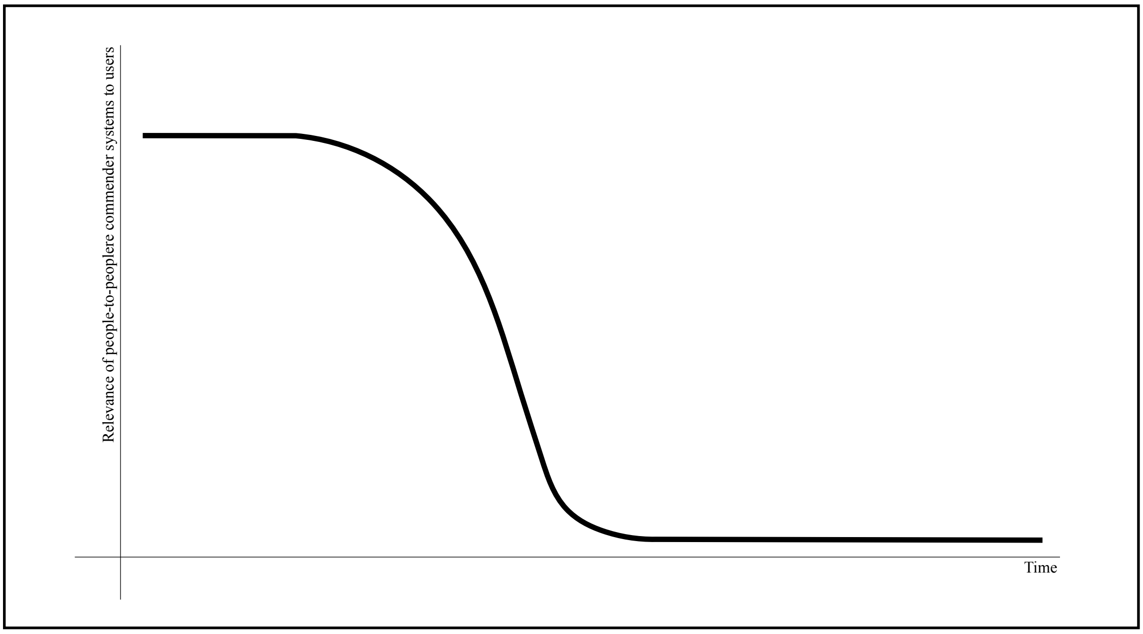


Figure 1. The relevance of people-to-people recommender systems decreases as users spend more time on a certain social network site.

6.1.1.New users

Even though the users who were interviewed were familiars with the SNSs used by them, they often compared their current perceptions about social network sites and people-to-people recommender systems, and their own experiences at the moment when they started using these services. As recalled by the interviewees, their first experiences on new SNSs environments (specially on those for social purposes, such as Facebook) were related to the creation of their own community, meaning that they started connecting to people who were known in real life, acquaintances and also strangers. One of the most common explanation for this behavior was related to a need of having as large number of connections as possible, as the number of friends would reflect their own popularity out of internet context (such as at school, for example).

At this first moment, users reported to pay more attention to people-to-people recommendations, as they were building their own network on SNSs. Supposedly, the recommendations presented at this first moment also seemed to be more relevant and adequate to the goals of users back then.

> "[Have you ever added or followed someone you didn't know from those recommendation lists?] Yes, of course. When I was new on Facebook. I felt like I needed to have more friends. So I would add, like friend of friends, who I think was cool and I would meet eventually. But rarely completely unknown people." [Woman, 25 years old, in a relationship]

6.1.2.Middle experiences

a. Irrelevant recommendations

Following the first stage, when users utilize people-to-people recommender systems intensively, the interviewees reported that the recommendations started becoming irrelevant, as less and less of the people recommended would be interesting or known by them. Another point that can be observed at this phase is the goal of users towards SNSs, as it may also differ from the previous phase.

According to the interviews, as users got older and more used to the new SNS, the need of expanding their social network in that new environment decreases. The reasons behind this new behavior may be related to either 1) a change of values or environment, such as leaving school and disregards upon social pressures regarding the number of friends online (as in having online connections to succeed socially in school); in addition, 2) this behavior can also show that users eventually reach a social saturation as more and more connections are added to their network. As users reach this saturation, new connections may become less attractive, affecting their perception on people-to-people recommender systems at the same time.

b. Negative experiences

A common concern, especially among the women interviewed, is online harassment on social media. According to the interviewees, it is common for them to receive friend requests from unknown men without any friends or interests in common, also from remote regions, other than they have ever visited or lived in. In addition, some interviewees mentioned private messages with sexual or romantic connotations sent by these same profiles. As related by interviewees, these messages arrive without requests or previous conversations, that would denote an interest in establishing a sexual relationship with the sender: "I used to have my company, and I had a page on Facebook and random people sending me messages. 'Hey pretty, what are you doing today?'" [Woman, 31, in a relationship].

There were no mentions about online harassment from male interviewees.

6.1.3.Ignoring phase

The called *Ignoring phase* was the last one identified among the interviewees, as most of them behave similarly towards people-to-people recommender systems on SNSs. As the name of this phase suggests, users at this stage share a tendency to ignore new recommendations of users to connect with, mostly based on past experiences (both negative experiences with recommendations of strangers, and the exposure to irrelevant suggestions, as seen in the last section). At this point, users have reported to be satisfied with their networks on social media and not actively looking for new connections. Therefore, people-to-people recommendations are often ignored while users browse through social network sites.

> "I have noticed, the people, who are suggested to me, we have several common friends, but most often I don't know those people, or we have met at one party and just said "hello" or so. I never really care for that. I just close the window." [Woman, 31 years old, in a relationship]

6.2. More information and common interests increase attractiveness

Access to information is one of the key-points regarding recommender systems. When used in e-commerces or streaming platforms, for example, users usually get access not only to recommendations, but also characteristics that would make those recommendations relevant (such as product attributes, brand, functionality or content). However, on the context of social network sites, the information included in profiles that are recommended is usually limited, as users themselves may impose limits to the information that is disclosed publicly.

During the interviews, when discussing about what makes a profile interesting, the interviewees related that *having interests in common* is one of the key factors to consider adding another user suggested through social matching systems. On the other hand, when questioned about reasons to ignore or reject a suggestions, the responses were almost unanimous: the difficulty in finding common interests or connections when looking at the suggestions.

The fear of online harassment also plays an important role in ignoring suggestions, specially among the women interviewed. The lack of information in some profiles may increase the feeling of uncertainty and decrease how attractive a profile is. In like manner, the propagation of so called *bots* (profiles controlled by computer, usually used with spam purposes), may also support the resistance towards empty profiles, since some users reported concerns of having data stolen by these profiles.

6.2.1. Online encounters empower users

The process of approaching people differs from when it happens face-to-face or in a virtual environment. According to the users interviewed, the process of interacting with someone new, or barely known, can be considered easier online, as the users have the opportunity to think about what to say, or even research more about the topic being discussed. The fact of not being physically present eliminates the need of an answer straight away, in a way that the parties involved in a conversation are able to perform other activities at the same time.

> "I think it is easier to approach online, because you have more time to prepare for writing a message and to think about things, and to answer. You don't have to give the message instantly in the face of the person, and you have to think everything quickly. I think you can prepare more for the conversation." [Man, 27, in a relationship]

> "Well, online there's the comfort of being in your own house, so you are at your safe environment, more relaxed, and you just chat. You don't have to worry about your body language and your appearance, so I guess that would change the way people communicate." [Woman, 31, in a relationship]

On the other hand, online approaches may reduce the perception of proximity or humanity between the parts, as the interviewees related a lack of real emotions and reactions in conversations carried virtually. As mentioned by one of the interviewees,

> "Although you have your picture in your profile […] you are still some kind of anonymous. And you have some kind of distance with the other person. So you won't see her or his reactions. It is more neutral, the situation. I think it's not so personal." [Man, 34, single]

Related to the lack of physical contact and trust, some interviewees also mentioned trust issues regarding the real appearance of unknown people who were met online. The common belief about this matter is that the pictures available online may not completely represent the person on the other side. Furthermore, a static picture is not able to truly represent the personality or manners of the other person.

Communication is considered trustworthier face-to-face than online, as users believe that a face-to-face dialogue may inhibit and prevent others from lying. As a downside, these situations may increase negative feelings, such as anxiety, as there is more pressure to keep the conversation flowing naturally with less time to reflect. These situations are said to be more uncomfortable, relying on more or less social skills of an individual. However, there is a belief that starting communication online may ease conversations face-to-face between two (or more) users established in the future, since they are able to find tastes and interests in common, or even search more about each other's preferences beforehand.

In addition, according to the interviewees, having information about unknown people beforehand (i.e., by starting a relationship online before meeting in person in a second moment) helps and eases the establishment of conversations in a face-to-face situation. By knowing personal tastes and preferences, for instance, the interviewees related more confidence to talk in person to people who they barely know or do not know at all. Furthermore, it is important to notice that social recommender systems give limited information about the suggested profiles, covering mostly basic information, such as connections in common, city of residence and school. However, considering the usage of social media on mobile phones, most information is only accessible after selecting and exploring the profiles, which the majority of interviewees said not to do.

6.2.2. "I don't trust people recommended to me"

During this research, it became clear the differences between traditional recommender systems, such as the ones used on e-commerces and streaming websites, and people-to-people recommender systems utilized on social network sites, regarding trust of users in both system and recommendations.

First of all, recommender systems utilized by e-commerces, for example, offer products to be consumed by the user, in a sense that the user may interact with something unanimated, such as a new book or movie (i.e., objects unable to think or have an own opinion). On the other hand, people-to-people recommender systems regard two animated agents who must share common interests (such as the connection itself) in order to be a successful recommendation.

Second, even though experiences of people towards products may differ based on several aspects (e.g., familiarity, expectations and skills), products made in large scale are usually the same, meaning that consumers may expect something from it based in an expected functionality. As an example, when buying a movie, the customer has access to a synopsis, that present may elements of that movie. On the other hand, people are mostly unpredictable and users of social network sites are not able to define clear outcomes of a connection.

These factors were also reflected during the interviews with users of SNSs. When questioned about trusting the people recommended through social matching systems, all the interviewees affirmed not to trust the people recommended, as they are usually not familiar or known in real life. According to the users, the fact of being recommended by an automatized system does not grant credibility to the profiles recommended, since the person behind each profile is still unknown.

Nevertheless, trust may have stronger or weaker effects on users decisions, depending on different social network sites. The next subchapter presents differences between the most utilized SNSs among the interviews.

6.3. Different SNSs affect how people-to-people recommendations are perceived

The use and relevance of recommendations given through social matching systems in social media seemed to vary among different SNSs. The strongest contrast can be perceived between the recommendations on LinkedIn and Facebook. According to the interviewees, people recommendations on Facebook become mostly irrelevant soon after the creation of their accounts in the SNS, while LinkedIn users reported a continuous interest in expanding their professional networks online.

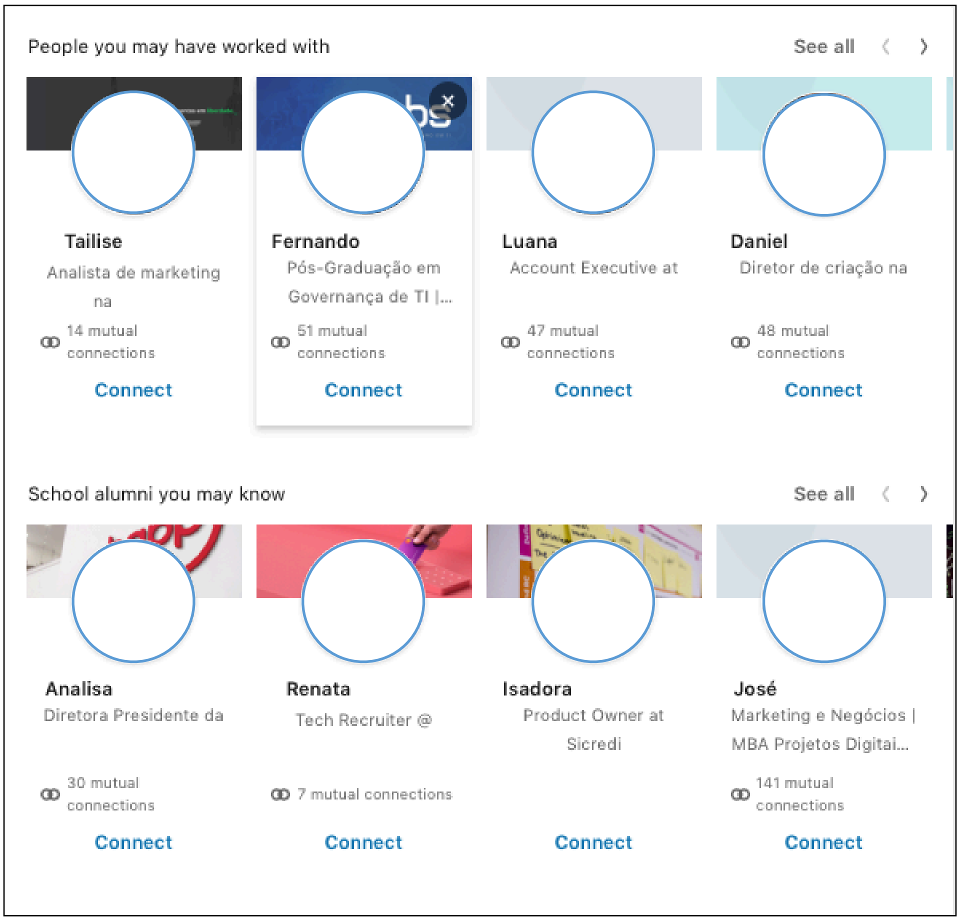
6.3.1.LinkedIn

LinkedIn (*www.linkedin.com*) is a social network site with professional purposes, such as developing networking and finding job opportunities. The SNS is used worldwide, connecting professionals of different countries and fields. Contradicting the common behavior towards people-to-people recommender systems (when users become unaware of them), users reported a constant interest in expanding their networks on LinkedIn, continuously paying attention to users that are recommended. This behavior can be related to an expectation of getting something else other than only social connections (or "Friends") from the SNS, such as job and business opportunities. Also, some interviewees consider LinkedIn users more reliable (or trustworthy) than users in other SNSs.

> "LinkedIn suggestions are more professional. It seems more reliable. [What do you think that makes it seem more reliable?] I think if a person has a proper job, it means that is more reliable than some random people from Facebook." [Woman, 25 years old, in a relationship]

According to the interviewees, an interesting profile on LinkedIn is made of interesting or similar careers to their own and valuable connections (meaning that the friends of the user recommended become potential connections). The main point about exploring profiles on LinkedIn was highly linked to professional opportunities and a way to be aware of novelties in the working *world* that the user is insert in. In a way, LinkedIn works in the adult life as a vitrine for professionals, where they can also expose their own experiences and competences. During the interviews, there were few explicit mentions regarding the written content made by potential new connections.

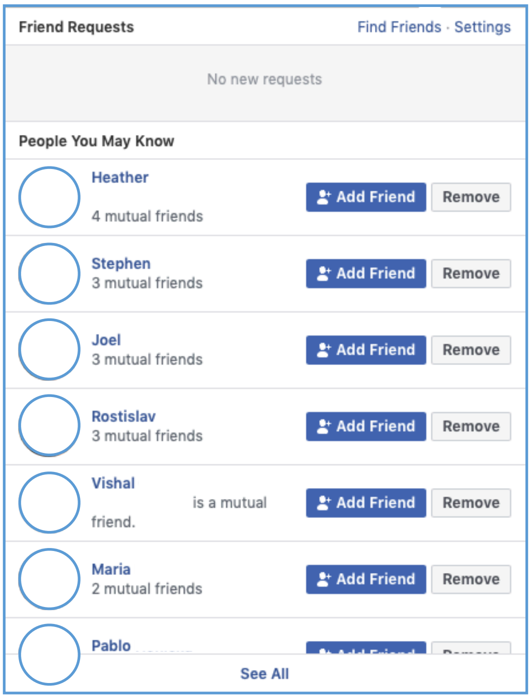
The users who were interviewed also present less concerns regarding privacy. This behavior leads users to filter potential connections in much less intensity than when compared to other SNSs with more personal characteristics, such as Facebook and Instagram.



Picture 2. People-to-people recommendations on LinkedIn. Modified by the author to keep the anonymity of users.

6.3.2.Facebook

Facebook (www.facebook.com) is one of the most used SNS in the world. It started connecting students among the United States and quickly evolved to new users outside university campuses. The main purpose of this SNS is to connect people, who can share life updates by uploading pictures and text to their profiles.



Picture 3. People-to-people recommendations on Facebook. Modified by the author to keep the anonymity of users.

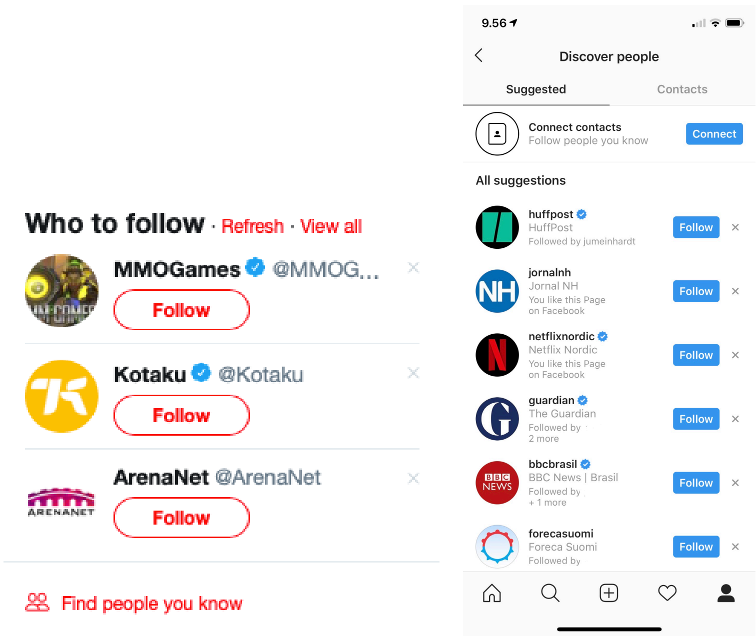
Facebook was also the social network site mostly used by the interviewees and the one with biggest resistance towards new connections with unknown people. Even though some interviewees suggested that they would be open to unknown profiles with common interests, such as hobbies, they still consider Facebook as a social network for closer friends and family, other than to know new people.

> "I've only checked [suggested profiles] sometimes if I see the face and I think that I kinda of know the person, who is it, then I click on the mutual friends, so I see who I know, which contact we share, so that I can remember where I may have met them, but that is all." [Woman, 31, in a relationship]

However, accumulating social capital through Facebook is not enough, as users expressed mostly no interest in expanding their network on Facebook. Meanwhile, users on LinkedIn had expectations of getting something else in return, other than just social connections in a virtual environment. As LinkedIn offers the possibility of expanding professional networking and access to job positions (both resulting in financial gains), social capital on Facebook is limited to interpersonal relationship in the most basic form, while is mostly interesting for younger users (as inferred from the changes of attitude of users from their first years on Facebook and current perceptions).

6.3.3.Instagram and Twitter

Instagram (www.instagram.com) is a SNS launched in 2010, where users can upload pictures and videos, both privately and publicly, permanently or temporarily, to their followers. This SNS was initially developed for smartphones, and its main functions are still limited to the mobile application (e.g., photo and video uploads). On the other hand, Twitter (www.twitter.com) was launched in 2006 as a microblog, where users could write short text entries up to 140 characters. Nowadays, Twitter also supports multimedia content. In both SNSs, users are invited to follow profiles of interest, while users can accumulate followers or selected them (by making a private account, that requires an authorization before following an account).



Picture 4. People-to-people recommendations on Twitter (left) and Instagram (right). Modified by the author to keep the anonymity of users.

During the interviews, Instagram users related that, when looking for new profiles to follow, they usually look for users who share a certain type of content, such as specific types of photography, hobbies or crafting, for example. Therefore, an interesting profile is defined by different styles and types of photography and eventually the texts that follow the images. As some interviewees related, an interesting profile on Instagram is a profile that shares images (or content) that is pleasant and match the own taste of the users. On Twitter, the sharing of interests is very similar to Instagram, as users may check the style of *tweets* posted, rather than the proximity with the person suggested itself.

> "On Instagram I follow people that I find their concept, like what is the text that goes with the photo, inspiring, or if their pictures are… How they stylize the photos, if t's inspiring to me. But on LinkedIn, I only send to people I've met through projects, studies or work, that I want to continue having some interaction with, so that I have more connections and more people see my profile, so I can have more chances of appearing in searches." [Woman, 31 years old, in a relationship]

In the context of people-to-people recommender systems, Twitter and Instagram also seem to fail delivering good or relevant recommendations. In these cases, the recommender systems adopted by these SNSs search mostly for profiles followed by other users and friends in common, in addition to connections from other SNSs (i.e., Instagram shows profile owned by Facebook friends). In such cases, the content shared by these users come in second plan. It is important to mention however an initiative from Instagram, that suggests posts based on last posts liked by the user. Nevertheless, this initiative was not mentioned by any interviewees, but recommendations created and propagated by users themselves.

> "[On Instagram, how do you get to those profiles that inspire you?] Most often, [they] are suggestions from people I follow. Like, people I follow, they share on their stories. They can suggest other accounts, that they like. So I check from there, then I see. If there is something I like, then I start following them." [Woman, 31 years old, in a relationship]

So to mention, related to Instagram, some interviewees also reported actions started by this SNS's own community, when users themselves started suggesting other accounts for their users through the functionality *Stories* (temporary posts that remain in a profile for 24 hours). Similarly, users on Twitter also used to recommend profiles in an individualized way through the so called *#FollowFriday*. As the name suggests, on Fridays, Twitter users would suggest other accounts to be followed by their followers. Even though this practice were not mentioned by any interviewees, it does relate to the practice adopted on Instagram (and mentioned by interviewees).

7. Discussion

7.1. The social impact of people-to-people recommender systems

Social matching systems do not seem to have a direct psychological effect on users of social network sites, as first considered during the early stages of this research. However, social matching systems do have a large impact on the general experience that their users will have utilizing SNSs where these systems are utilized.

During the interviews, it became clear that social matching systems are likely to become irrelevant to users over time, being as well ignored by them in many cases after a period of time being exposed to recommendations. In addition, interviewees' mentions about bad experiences regarding these systems were rare. As an illustration, even recommendation of antagonists (i.e., people who interviewees disliked) appeared to have low to none effect on users. In the most extreme cases, users revealed that their only action was to delete a disturbing recommendation, which did not appear again in the future. These findings relate to studies on subject of online harassment and cyberbullying, that showed a stronger tolerance of SNS users towards negative behaviors online [Jones and Mitchell, 2016; Lwina et al., 2012; Wolak et al., 2007]. To put in other words, victims of online harassment may often disregard (or ignore) bad behavior of other users towards them.

Despite the low engagement with social matching systems in later stages utilizing SNSs, it is possible to identify a stronger impact on the way that users utilize and perceive social networks sites in long term. The higher intensity of usage of social matching systems at the creation of a profile, for example, leads the user to connect to a higher number of people in a short period of time. According to the interviewees and based on observations, it is also possible to identify a stronger inclination to add more people by younger users, due to social pressure to be popular. Among the people added by younger users, it is also possible to infer that there may be a bigger proportion of contacts who are barely or completely unknown offline.

The high utilization of people-to-people recommender systems in early stages allows users to expand their network rapidly, working as a way to increase their social capital (as earlier explored in *Section 4.1.1.*). As a quick recapitulation, social capital regards the benefits that one can get from interpersonal relationships. As seen during the interviews, in a school context, having a large number of connection os SNSs may supports one's popularity among other students. Research conducted by Kim et al. [2011] have shown that students use SNS to expand their social network, while Manago et al. [2012] presents a growing average number per user on SNSs during school years. Concomitantly, their research shows that the increasing average of friends is not because students are having more close friends, but opening their social media profiles for acquaintances and virtual friends.

The contact with these people on social media, such as Instagram and Facebook, may lead users to negative feelings in later stages using these SNSs. As seen in literature, users have a tendency to publish "better realities" on social media, excluding negative or unattractive content. In a context limited to online interaction, a user may feel depressed when comparing their own lives to the other ones published online by acquaintances, and even believing that their own reality is not as attractive as the others [Lup et al., 2015; Krasnova et al., 2013; Gonzales and Hancock, 2011; Attrill and Jalil, 2011; Ong et al., 2011; Amichai-Hamburger and Vinitzky, 2010; Mehdizadeh, 2010].

Throughout this thesis, it was possible to identify that the social matching systems currently adopted by SNSs must be improved in order to keep their relevance to users in different stages of use. The following subchapter presents suggestions of improvements to social matching systems adopted by social network sites.

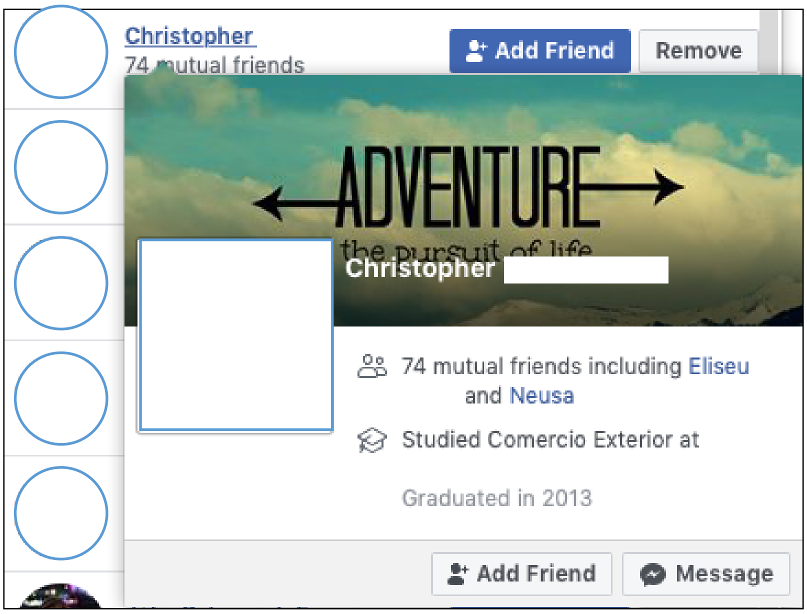
7.2. Design implications

7.2.1. More information about recommendations increase trust

Most social network sites clearly present (and base) their recommendations on mutual connections that an active user shares with the users who are recommended. The triadic closure process previously introduced (see *Section 3.3.1*) states that two parties with weak ties, that share strong ties with a third party, have bigger chances of developing a new relationship among them. A similar finding in Donath and Boyd [2004] states that sharing mutual connections with a stranger increases the trust in a recently established relationship. However, both factors do not satisfy users regarding people-to-people recommendation systems, as seen in the interviews conducted throughout the present thesis.

As seen in Pizatto et al. [2012], transparency, or reasoning, is one of the key factors to increase trust in recommendations, meaning that users value to understand in what recommendations are based. Meanwhile, the interviewees believe that social media, such as Facebook, fail to present clear points, other than mutual connections, that would make a recommendation more appealing to its users. Therefore, users of social network sites should have access to more information, that would help them to understand why a recommendation is relevant, and why they should pay attention to a recommended profile.

Currently, social network sites, such as Facebook, only present a limited amount of information about a recommendation, such as friend in common. Other information (e.g., city of domicile, school, work and hobbies) is usually limited to what the user, who is recommended, is willingly to share with others on the SNS. At the same time, an increasing apprehension about privacy and disclosure of sensitive information among SNSs users affect the availability of information disclosed publicly, as more people start caring about limits between public and private affairs [Chen, 2018; Chen and Chen, 2015]. Also this behavior reinforces a disbelief (and fear) that some users face regarding social network sites, as many do not feel comfortable in sharing personal information within the network.



Picture 5. Details about recommendations on Facebook. Modified by the author to keep the anonymity of users.

7.2.2.Clear common interests between parties increase appeal

As seen in Feld [1981], people who share common interests, such as hobbies, have more chances of developing stronger ties than those without any shared activities. Similarly, the users of SNSs clearly expressed during the interviews that their interest in people-to-people recommendations increased in case both user and recommendee (the user recommended) clearly share common interests and activities. However, this factor also concerns self-information disclosure and privacy issues, and must be considered when designing social matching systems for SNSs. Another point to be considered, specially regarding common interests and access to more information, is how much users are willingly to disclose in order to receive better and more complete recommendations.

7.2.3.Proven identity increases sense of security

Trust is a clear issue regarding social matching systems, as users report not to trust recommendations of people in social network sites. Among the main reasons for this lack of trust upon unknown people are the fear of being harassed online, or cyberbullied, fake profiles and or misrepresentations of personalities (such as hidden intentions). At the same time, as users have less access to information about other users, as already explored earlier, the whole experience within social network sites and people-to-people recommendation system is affected. In addition, when a user shares friends in common with a recomendee, these fears seem to decrease in intensity. However, less fear differs from trusting a recommendee. To put it differently, being aware of friends in common do not establish a relationship of trust between user and recommendee.

Picture 6. Verified badge (blue circle with "correct" mark following the name of the user) used on a verified profile from Facebook.

Even though little can be done to establish trust between to unknown people in a virtual environment, there are alternatives to reduce the feeling of vulnerability of users facing recommendations on SNSs. As an example, business pages and celebrities on social media already have access to badges that certifies the authenticity of a profile, meaning that the real person (or owned) is behind a profile, and that it is not being impersonated by someone else. A next natural step would be to expand this functionality to ordinary profiles, as already done in some services, such as Airbnb, where users can verify their profiles by uploading an image of an official document.

Another example of functionality that could reduce users' anxiety towards unknown profiles would be testimonials of friends regarding such person. This functionality, as the verified profile badges, is already used by some social network sites, such as Orkut (discontinued in 2014) and LinkedIn (with professional testimonials about workers' competences).

7.2.4. Conscious recommendations may improve overall user experience

The last point regarding improvements in people-to-people recommender systems addresses the problem of over usage of these systems during the first stages of a user in a social network site (also known as networking-building phase). As seen in *Chapter 6*, users have a tendency to use intensively people-to-people recommender systems when they start their accounts in a new SNS. Following the creation of account, users start building their own virtual network of friends and acquaintances, highly influenced by people suggested to them. As reported by the interviewees, especially regarding the use of social media during school years, they felt encourage to send requests of connection not only to friends, but also to strangers, motivated by a desire of being more popular and accumulate a larger amount of relationships online (as it would reflect in their lives outside of the web).

Considering the dangers, such as online harassment, that many users (specially young ones) are exposed to while sending friend requests to unknown people, suggested by recommender systems, requires special attention from designers of people-to-people recommender systems. It is important to keep in mind that not every recommendation, as of now, is truly relevant or trustworthy, and therefore users should be warned about dangerous of uncontrollably sending friend requests to strangers. More than that, recommender systems should impose limits to recommendations and deliver in portions, extending its relevance and diminishing chances of negative experiences within SNSs in the future.

8. Conclusions

This thesis aimed to understand the behavioral impact that social matching systems in social network sites have in its users. At first, this research had as a hypothesis that such systems could impact directly how new relationships are developed, since users may receive suggestions of unknown, but interesting profiles. However, the interviews with users implied that first hypothesis wrong, as it was possible to identify that the social matching systems currently adopted by SNS are mostly ignored by users in the course of time. As appointed by interviewees and inferred from literature, current social matching systems may fail to keep their relevance towards users due to 1) irrelevant recommendations, 2) limited information about people being recommended (also impacted by limitation to prove veracity of identities), and 3) large number of suggestions disregarding reciprocity of interest. Therefore, this thesis identified that these systems must be improved in order to keep their relevance to users over time (as seen in *7.2 Design implications*).

In the final analysis, it is important to underline the limitations faced throughout this thesis. First of all, it is important to draw a special attention to the profile of interviewees. It is believed that the homogeneity of users interviewed had a strong and direct impact on the results presented in this work. As previously seen in Findings (Chapter 6), user's perceptions on recommender systems changes over time, becoming more and more irrelevant after the networking-building phase, as seen also in Guy's work [in Ricci et al., 2015]. Nevertheless, the analysis upon earlier stages of SNSs utilization by the interviewed users relied exclusively on memories of interviewees, what can either give a wider perspective about how their experiences changed in the course of time, or a limited vision of earlier stages, as memories tend to fade over time.

Altogether, further research can be conducted regarding the utilization of social matching systems in social network sites, specially from users' perspectives. The present thesis proposes further research aiming to understand 1) the reliability of social recommender systems, 2) safety concerns regarding the usage of such systems by underage users, 3) the efficiency of professional matching systems, and 4) how people-to-people recommender systems may be utilized by different cultures.

First of all, several recommender systems theories mention the feeling of trust that recommendations cause on users. This research found out that, considering social recommender systems, the trust factor is not inherent to recommendations of people. As a matter of fact, users understand that trust does not apply completely to recommendation of strangers. However, information, such as friends in common, may reduce the sense of safety (even if still does not configure as trust).

Secondly, as the interviewed users related to add more strangers in social media during early stages of life, it urges the importance of studying and developing trustworthier social recommender systems, considering this profile of users and their vulnerability in the internet. Such connections tend to remain on user profiles in later stages, taking part on news feed and eventually leading users to feel annoyed, as users mentioned "not to care" about the updates published by these connections. However, at the same time, users do not seem to take action towards these profiles (such as deleting), what can be related to a fear of reducing their audiences and impacting their social capital.

Third, as identified during the interviews, most of connections established on LinkedIn remained without further or deeper interaction between parties (e.g., private messaging or networking). Still, users actively mentioned more attention to recommendations on LinkedIn than other social medias. Therefore, more research could also be conducted regarding the use of social recommender systems and professional *matchmaking*, as a potential area of development and exploration for business and academia (i.e., interaction *stimuli*).

At last, this research found some indicatives that the use (and relevance) of people-to-people recommender systems may differ according to distinct cultures. In the present case, two Brazilian users identified as male have shown higher interest and attention to recommendations, even in later stages of SNS utilization, contradicting other interviewees, who did not share the same nationality. Further research could possibly explore in more depth how people-to-people recommender systems are perceived and used by Brazilian SNSs users.

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APPENDIX 1

RESEARCH SCRIPT

PART 1: COMMUNICATION & SOCIAL MEDIA

1. Present yourself, age, occupation, relationship
2. How do you usually communicate with family, friends and acquaintances?
3. How often do you utilize social media?
4. Which is your favorite social network and why?
5. What would you say are the main reasons for you to keep using the social medias you use?
6. What are your favorite functionalities or what do you use more often in these medias?

PART 2: NEW RELATIONSHIPS

7. What is the difference between getting to know someone online or offline?
8. In your opinion, how social media could be used to meet new people?
9. What do you think about friend/follow requests from unknown people?
10. What would you motivate to accept or deny these requests?
11. What is the difference between following/being followed by someone you do not know and adding/being added as a friend by someone you do not know?

PART 3: SUGGESTIONS

12. What do you think or feel about the suggestions of people to follow or to add as a friend?
13. How do you think those users are suggested for you?
14. What do you usually do with (or how do you use) the suggested profiles?
15. Have you ever spotted changes in these suggestions?
16. Why, in your opinion, these changes happened?
17. Have you ever deleted any suggestion? Why?
18. What makes these suggestions interesting, or not?
19. Have you ever send a friend request or followed someone on these lists? Why?
20. Have you done it to someone you didn’t know beforehand? Why?
21. What is your attitude if you don’t know someone that looks “interesting”, but Facebook tells you that you both have friends in common?

NOTE: Ask to open the pages/apps in the favorite device.

22. Do you perceive differences in suggestions among the social medias you use? Which?
23. How do you feel in general about the suggestions to follow and to add as a friend?

PART 5: INFORMATION SEEKING

24. Have you ever searched for more informations about the people suggested to you? Why?
25. Do these searches evolve to other social networks or search platforms? Why or in which circumstances?
26. What informations you look for during these searches?
27. How did it impact your decision or attitude towards the person?
28. How do you behave when meeting those people suggested for you in person?
29. How do you feel knowing informations about the person beforehand?
30. What is your opinion about the following affirmation:
    "*I TRUST THE PEOPLE RECOMMENDED TO ME*"
31. What would increase your trust in these recommendations?

APPENDIX 2

INTERVIEWEE RECRUITMENT FORM

BRIEFING: Hi! I am a student from Tampere University and I am conducting a research for my master's thesis about social medial usage. I am interested in understanding your perceptions about the social media you usually use, and also how these websites impact your daily life. All the personal data gathered during this research is handled anonymously and your identity will not be shared with other people. The interview will last for approximately 30 minutes and you can decide to stop at any time. I have now a couple of questions to understand a little bit more of your profile.

GENDER: ( ) MALE ( ) FEMALE ( ) OTHER: _____________ **AGE:** _________
RELATIONSHIP: ( ) SINGLE ( ) MARRIED ( ) DATING ( ) OTHER: _________
NATIONALITY: ____________________ **MAIN OCCUPATION:** ____________________

HOW MANY HOURS A DAY (APPROXIMATELY) YOU SPEND IN SOCIAL MEDIA? _______

IN WHICH DEVICE DO YOU MOSTLY ACCESS YOUR SOCIAL MEDIAS? (ONE CHOICE)
( ) DESKTOP ( ) LAPTOP ( ) TABLET ( ) MOBILE ( ) OTHER: ____

WHICH SOCIAL MEDIA DO YOU USE REGULARLY? (MULTIPLE CHOICES)
( ) FACEBOOK ( ) INSTAGRAM ( ) TWITTER ( ) LINKEDIN ( ) SNAPCHAT
( ) TWITCH ( ) SWARM ( ) STRAVA ( ) TUMBLR ( ) PINTEREST
( ) NIKE ( ) FLICKR ( ) OTHERS: ______________________________

DO YOU RECALL SUGGESTIONS OF USERS MADE BY THESE SOCIAL MEDIAS? (1 CHOICE)
( ) YES ( ) NO ( ) I AM NOT SURE

INTERVIEWEE CODE: ____________