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Mediating chance encounters through opportunistic social matching

Julia M. Mayer
New Jersey Institute of Technology

ABSTRACT

MEDIATING CHANCE ENCOUNTERS THROUGH OPPORTUNISTIC SOCIAL MATCHING

by
Julia M. Mayer

Chance encounters, the unintended meeting between people unfamiliar with each other, serve as an important social lubricant helping people to create new social ties, such as making new friends or finding an activity, study or collaboration partner. Unfortunately, social barriers often prevent chance encounters in environments where people do not know each other and people have to rely on serendipity to meet or be introduced to interesting people around them. Little is known about the underlying dynamics of chance encounters and how systems could utilize contextual data to mediate chance encounters. This dissertation addresses this gap in research literature by exploring the design space of opportunistic social matching systems that aim to introduce relevant people to each other in the opportune moment and the opportune place in order to encourage face-to-face interaction. A theoretical framework of relational, social and personal context as predictors of encounter opportunities is proposed and validated through a mixed method approach using interviews, experience sampling and a field study of a design prototype.

Key contributions of the field interview study (n=58) include novel context-aware social matching concepts such as: sociability of others as an indicator of opportune social context; activity involvement as an indicator of opportune personal context; and contextual rarity as an indicator of opportune relational context. The following study combining Experience Sampling Method (ESM) and participant interviews extends prior research on social matching by providing an empirical foundation for the design of opportunistic social matching systems. A generalized linear mixed model analysis (n=1781) shows that personal context (mood and busyness) together with the sociability of others nearby are the strongest predictors of people's interest in a social match. Interview findings provide novel approaches on how to operationalize relational context

based on social network rarity and discoverable rarity. Moreover, insights from this study highlight that additional meta-information about user interests is needed to operationalize relational context, such as users' passion level for an interest and their skill levels for an activity. Based on these findings, the novel design concept of passive context-awareness for social matching is put forward.

In the last study, *Encount'r,* an instantiation of an opportunistic social matching system, is designed and evaluated through a field study and participant interviews. A large-scale user profiling survey provides baseline rarity measures to operationalize relational context using rarity, passion levels, skills, needs, and offers. Findings show that attribute type, computed attribute rarity, self-reported passion levels for interest, and response time are associated with people's interest in a match opportunity. Moreover, this study extends prior work by showing how the concept of passive context-awareness for opportunistic social matching is promising.

Collectively, contributions of this work include a theoretical framework encompassing relational, social, and personal context; new innovative concepts to operationalize each of these aspects for opportunistic social matching; and field-tested design affordances for opportunistic social matching systems. This is important because opportunistic social matching systems can lead to new social ties and improved social capital.

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by
Julia M. Mayer

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APPROVAL PAGE

MEDIATING CHANCE ENCOUNTERS THROUGH OPPORTUNISTIC SOCIAL MATCHING

Julia M. Mayer

Dr. Quentin Jones, Dissertation Advisor Associate Professor of Information Systems, NJIT	Date
Dr. Starr Roxanne Hiltz, Committee Member Distinguished Professor Emerita of Information Systems, NJIT	Date
Dr. Cristian Borcea, Committee Member Associate Professor of Computer Science, NJIT	Date
Dr. Michael Ehrlich, Committee Member Associate Professor of Management, NJIT	Date
Dr. Kaisa Väänänen, Committee Member Professor of User Experience, Tampere University of Technology, Finland	Date

BIOGRAPHICAL SKETCH

Author: Julia M. Mayer

Degree: Doctor of Philosophy

Date: May 2016

Undergraduate and Graduate Education:

- Doctor of Philosophy in Information Systems,
  New Jersey Institute of Technology, Newark, NJ, 2016
- Master of Science in Information Systems,
  New Jersey Institute of Technology, Newark, NJ, 2010
- Bachelor of Science in Information Engineering,
  Hamburg University of Applied Sciences, Hamburg, Germany, 2005

Major: Information Systems

Presentations and Publications:

Mayer, J.M., Hiltz, S. R., Barkuus, L. Väänänen, K. & Jones, Q. (2016). Supporting Opportunities for Context-Aware Social Matching: An Experience Sampling Study. *Proceedings of the 34th Annual ACM Conference on Human Factors in Computing Systems*. New York, NY, USA.

Mayer, J.M., & Jones, Q. (2016). Encount'r: Exploring Passive Context-Awareness for Opportunistic Social Matching. *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work & Social Computing*. New York, NY, USA.

Mayer, J. M., Hiltz, S. R., & Jones, Q. (2015). Making Social Matching Context-Aware: Design Concepts and Open Challenges. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 545–554). New York, NY, USA.

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Mayer, J. M., Motahari, S., Schuler, R. P., & Jones, Q. (2010). Common attributes in an unusual context: predicting the desirability of a social match. In *Proceedings of the 4th ACM Conference on Recommender Systems* (pp. 337–340). New York, NY, USA.

Für meine Mutti,
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bei all meinen verrückten Ideen, Projekten und Reisen unterstützt.

"Ha, des musch macha!"

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who always, unconditionally, and full of love,
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CHAPTER 1

INTRODUCTION

1.1 Research Problem

Every day we cross paths with numerous strangers. Without us knowing, these people might just be that tennis partner we have been looking for, the ideal partner for a political discussion, or the Spanish tutor we need so desperately. While we may not be aware of these nearby individuals, our smart phone can be.

Chance encounters, the unintended meetings between people unfamiliar with each other, serve as an important social lubricant helping people to create new social ties, such as making new friends or finding an activity, study or collaboration partner. Life provides many opportunities for chance encounters – on a flight, waiting in line at the supermarket, and on the train to work, to name a few. While we often are surrounded by interesting people, it is problematic to identify who they are and how to connect with them (Bandura, 1982). Social barriers are preventing chance encounters in environments where people do not know each other and we often have to rely on serendipity to meet or be introduced to interesting people around us. However, the number and strength of social network ties is important for people's mental health (Scheff, 1994) as well as people's academic success, with a significant relationship existing between first year university dropout rates and social connectivity (Wilcox, Winn, & Fyvie-Gauld, 2005).

As mobile social applications are becoming an essential part of our social fabric, they are transforming the way we make new social ties and redefining human connection and communication. Social matching systems aim at supporting the creation of new social ties by recommending people to people (Terveen & McDonald, 2005). In theory, such systems could decrease social barriers for initiating face-to-face interaction with an unfamiliar person and increase social capital. Instead, research suggests that existing mobile phones and social networking applications can lead to real world social isolation and a decrease in face-to-face encounters (Putnam, 2000; Turkle, 2011). A key challenge that we explore here is how to design applications that can effectively overcome this real-world versus digital-world divide.

Proximity-based social matching has made its way into numerous commercial mobile applications, especially mobile online dating applications, such as *Tinder*[1], *Grindr*[2], *or Happn*[3]. *Highlight*[4] is a commercial mobile app that is not explicitly for dating, but generally for finding interesting people nearby based on shared profile items and proximity. However, some people argue that generalized matching applications are doomed to failure because people do not want to meet random strangers for random things like having a drink or going to the cinema (Lomas, 2013). While there is some validity to this perspective, there are a multitude of situations in which generalized matching could be of value, for example, not having any friends at new university or workplace (Feld & Carter, 1998; Mollenhorst, Volker, & Flap, 2014). Moreover, some people might be more actively looking for ways to meet than others, such as expatriate communities, or conference attendees hoping to network.

Even though mobile social matching systems are increasingly used and attract attention from both academic and industrial researchers, there are still many challenges and opportunities to be explored and developed. A major issue is that most systems only consider profile similarity, shared social ties and geographical distance to recommend people (Beach et al., 2008; Eagle & Pentland, 2005; Terry & Mynatt, 2002). In addition, users are matched for a single clear purpose, e.g., "Connect me with nearby female singles" (*Tinder*[1]), or "Connect me with nearby available drivers" (ride-sharing application *Uber*[5]). Fewer, if any systems make use of a broader set of characteristics to find any worthwhile, relevant, or interesting people nearby for potential friendship and

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[1] http://www.gotinder.com (accessed Jan. 2016)
[2] http://www.grindr.com (accessed Jan. 2016)
[3] https://www.happn.com (accessed Jan. 2016)
[4] http://highlig.ht (accessed Jan. 2016)
[5] https:/www.uber.com (accessed Jan. 2016)

social activities.

Social matching systems currently do not have effective mechanisms to mediate chance encounters and introduce *relevant* people to each other in the *opportune* moment and the *opportune* place in order to encourage face-to-face interaction. Situations in which people are interested in chance encounters have not yet been effectively modeled, and therefore, system-building efforts have lacked a firm foundation. There is little empirical knowledge of user requirements, a general conceptual framework does not exist, and the efficacy of system design has not been empirically established. Beyond simple notions of similarity, proximity and social ties, we have limited knowledge about the underlying dynamics of chance encounters and how systems could utilize contextual data to mediate chance encounters.

1.2 Objective

The overall aim of this research is to find ways to mediate face-to-face chance encounters through mobile technology. This will be done by systematically studying various contextual factors that determine chance encounters. Theoretical and experimental work is required to understand how these factors are interrelated. Results of this research will enhance our understanding of people's context-dependent motivations to meet new people and how mobile technologies could mediate chance encounters through serendipitous introductions. Expected contributions include a theoretical model to predict contextually relevant introduction opportunities, as well as the principled design of new innovative design affordances for opportunistic social matching systems that mediate chance encounters by introducing people to each other based on contextual information in an intelligent and unobtrusive way.

1.3 Broader Impacts

Outcomes of the proposed research aim at improving people's ability to discover relevant people nearby and potentially build new social ties and create social capital. Opportunistic social matching systems that mediate chance encounters have the potential for entirely new possibilities for social navigation enabling people to create valuable relationships without explicitly seeking for specific people. Building new social ties is an important concern as individuals embedded in richly connected social environments are, for example, better able to handle personal setbacks such as financial failures and illness and to provide social support for others.

1.4 Dissertation Organization

This dissertation proceeds as follows. First, the dynamics, determinants and potential beneficial outcomes of chance encounters are explored from a sociological and psychological perspective. After that, technological concepts, such as context-awareness and recommender systems, that could potentially be used to mediate chance encounters are presented. Chapter 4 then discusses social matching systems in-depth, particularly the matching process as well as different matching approaches that related research has explored. Chapter 5 presents prior research conducted as part of the author's Master's thesis exploring the concept of contextual rarity in mobile social matching systems. Collectively, this leads to the proposition of a theoretical framework for opportunistic social matching (Chapter 6). Based on open challenges identified, Chapter 7 presents research questions and a research plan. In Chapter 8, findings from an interview study are illustrated. Chapter 9 presents findings of an Experience Sampling Study exploring the theoretical framework quantitatively, while Chapter 10 presents a research prototype of an opportunistic social matching system that was evaluated through a field study. The dissertation concludes with a discussion of outcomes and contributions and broader impacts in Chapter 11.

CHAPTER 2

DYNAMICS OF CHANCE ENCOUNTERS

The previous chapter claimed that chance encounters are rare but powerful incidents that connect unknown people with each other. However, researchers have only limited knowledge of their dynamics and therefore systems currently lack tools to support chance encounters. This chapter provides an in-depth discussion of chance encounters in order to gain a deeper understanding of their underlying dynamics. We define chance encounters and review related sociological and psychological research that shines light on determinants of chance encounters. We categorize determinants into *relational, social,* and *personal factors* and elaborate on each of them. The chapter ends with a discussion of potential beneficial outcomes of chance encounters, such as social tie formation and new social capital.

2.1 Defining Chance Encounters

The Merriam-Webster dictionary defines an *encounter* as "a meeting that is not planned or expected, usually brief experience with another person", i.e., any situation or occasion when two people see and talk to each other. In other words, an *encounter* is the intersection of paths between two people involving focused interaction through direct conversation or by being engaged in a common activity. In his 1982 essay, Bandura defines a chance encounter as an "unintended meeting of persons unfamiliar to each other" (Bandura, 1982).

2.1.1 Chance and Serendipity

By definition, a chance encounter happens *by chance*. The Merriam-Webster dictionary defines *chance* as both "something that happens unpredictably without discernible human intention or observable cause" (being synonymous with *luck*) or as "an opportunity to do something, an amount of time or a situation in which something can be done" (being synonymous with *opportunity)*. Thus, both *luck* and *opportunity* play important roles in chance encounters.

Chance encounters seem to rely on *luck*, because they are unexpected, unplanned and not engineered by either party (i.e., fortuitous) and therefore come with a surprise effect. At the same time, chance encounters rely on *opportunity*, meaning that two people have to be in a situation where their paths intersect and they have the opportunity to interact. Bandura (1982) argues that we cannot understand the complex social dynamics that are at play when chance encounters occur which is why they often seem random and unpredictable.

Chance encounters can further be described as *serendipitous*. Serendipity is defined by the Merriam-Webster dictionary as "luck that takes the form of finding valuable or pleasant things that are not looked for". An example of serendipity is stumbling across a valuable or interesting website while looking for something else on the internet. Prior research has stressed the need for technology supporting serendipity, e.g., in information retrieval to stimulate curiosity and encourage and support exploration (Toms, 2000).

When two people meet and start interacting by chance and the interaction turns out to be enjoyable, valuable, satisfying or pleasant in some way, we refer to it as a *successful chance encounter*. Whether a chance encounter is successful or not depends on the *collective benefit* of it - aggregating the individuals' perceived benefit of the encounter. In other words, a chance encounter was successful if either or both participants perceived the conversation as worthwhile; or at least one of them while the other one is neutral.

2.1.2 Technology in Chance Encounters

Chance encounters, in their traditional sense, are defined by *face-to-face* interaction, e.g., bumping into each other in the hall way and starting a conversation. Nowadays however, chance encounters could also be *computer-mediated*, e.g., coming across an unknown person on a social network site and initiating interaction. Computer-mediated communication (CMC) tools allow people to communicate through information systems, e.g., message systems like e-mail (Hiltz, 1993; Turoff, 1989). Social computing systems like blogs, social network sites, wikis, and social bookmarking, generally encompass some kind of CMC tool to support any kind of social behavior (Erickson, 2013) and can enable people to find and interact with unknown people online.

2.2 Relational Determinants of Chance Encounters

In the following sections we explore factors regarding the relationship between two people determining a successful chance encounter based on *Social Identity Theory, Similarity-Attraction* and *Complementarity Theories,* as well as theories of *Social Exchange, Uncertainty Reduction, Predicted Outcome,* and *Mere Exposure*.

2.2.1 Social Identity Theory

When encountering a stranger, people categorize themselves and others based on belonging to social groups, such as sporting clubs, fans of certain TV series, or members of a university (Tajfel & Turner, 1979). *Social Identity Theory* (SIT) assumes that behavior is based on self-conception of group membership, group processes, and intergroup relations (Abrams & Hogg, 1990). People's current situation defines their social identities and situationally generated roles as well as what they are both concerned about at the moment (Goffman, 1972). People belong to a number of different groups and as people traverse different contexts, different social identities, roles and attitudes become relevant (Ajzen & Fishbein, 1973; E Goffman, 1959). Roles and social group identities prescribe (1) with whom, (2) about what, and (3) how to communicate with others (Neuliep, 2011), and therefore, might motivate certain behavior, such as solidarity within our groups and discrimination against out-groups, with the aim to achieve positive self-esteem and self enhancement (Abrams & Hogg, 1988).

2.2.2 Similarity-Attraction and Complementarity Theory

Certain interpersonal characteristics define if a relationship is maintained after a chance encounter (Bandura, 1982). For example, mutual attraction can turn chance encounters into lasting relationships while mismatches of personal attributes may result in disinterest or rejection. The most common cliché about human nature is that *birds of a feather flock together* (Similarity-Attraction Effect) (McPherson, Smith-Lovin, & Cook, 2001). Homophily, "the love of the same", is the tendency of people to bond with others who are similar to them (McPherson et al., 2001). This is also referred to as *propinquity*, both the physical or psychological proximity between people (Nahemow & Powell, 1975). A possible explanation of the similarity-attraction phenomenon is that knowledge of similarity may help people to predict others' future behaviors and people expect that others who are similar to themselves have a greater chance of being attracted to them ("likeness begets liking") (Byrne & Nelson, 1965). Research has confirmed that people declared greater liking for and attraction to people who are like them in various areas, as listed in Table 2.1.

Table 2.1 Areas of Similarity Affecting Attraction

Similarity Type Affecting Attraction	Source
Basic values, interests and hobbies	*Davis, 1981*
Attitudes and values	*Byrne & Nelson, 1965; Jamieson, Lydon, & Zanna, 1987; Werner & Parmelee, 1979*
Personality characteristics (e.g., optimism, self-esteem, shyness, conscientiousness, intelligence)	*Byrne, Baskett, & Hodges, 1971*
Preferred activity	*Werner & Parmelee, 1979*
Ethnicity & culture (color, age, wealth, nationality, region of origin, education, religion)	*Osbeck, Moghaddam, & Perreault, 1997*
Socioeconomic status & demographic information	*Verbrugge, 1977*
Social habits (e.g., frequency of attending parties) and bad habits (e.g., drinking and smoking)	*Eiser, Morgan, Gammage, Brooks, & Kirby, 1991*
Common history and shared experiences ("familiar strangers")	*Paulos & Goodman, 2004*

Researchers have also explored the difference between the perceived and actual similarity and found that *perceived similarity* is more important than actual similarity (Montoya, Horton, & Kirchner, 2008). Along the same lines, Newcomb (Newcomb, 1956) found that similar characteristics only predispose attraction if the shared attributes are both *observable and valued* by those who observe them. Furthermore, similarity-attraction was found to be particularly strong in the form of solidarity when individuals recognize each other as belonging to the same minority group (Goffman, 1966; Osbeck et al., 1997). As an example of this, Goffman (1966) states that when fellow nationals meet in exotic lands they may feel obliged or privileged to initiate a conversation. Moreover, competition between groups fosters a strong sense of group identity and solidarity (Sherif, Harvey, White, Hood, & Sherif, 1961).

In summary, similarity is a strong and well-studied determinant of interpersonal attraction. However, it is not simply the number of shared attributes but various other factors that also influence similarity-attraction.

Another cliché about relationships is that *opposites attract*. Researchers have proposed the *complementarity view of attraction:* people may be more likely to be attracted to partners who complement rather than replicate certain attributes (Christopher & Horowitz, 1997; Winch & Ktsanes, 1954). An individual will be attracted to "*that person who gives the greatest promise of providing him or her with maximum need gratification*" (Winch et al., 1954, p. 242). People who are different in their personality may like one another because they would fill in the gaps present in one another's life or because they may not like others who share negative personality traits with them. Other research explored how dissimilar attitudes in interpersonal communication affect attraction and found that people with attitudinally dissimilar partners reported higher attraction than communication partners with similar attitudes (Brink, 1977; Lombardo, Weiss, & Stich, 1973; M. J. Sunnafrank & Miller, 1981).

2.2.3 Theories of Social Exchange, Uncertainty Reduction and Predicted Outcome

Bandura (1982) describes that encountered people or groups should possess some personal resources needed in order to have an impact (i.e., entry skills / milieu rewards). This can be explained through *Social Exchange Theory* (SET) (Emerson, 1976) that posits that people calculate the overall worth of a particular relationship by subtracting its costs from the rewards it provides, i.e. doing a subjective cost-benefit analysis before forming a social tie. *Costs* might be the effort put into a relationship (time, money) and the negatives of a partner, while *rewards* are the elements of a relationship that have positive value (e.g., a sense of acceptance, support, and companionship). Research has found that reciprocal rewards are key for social tie formation. For example, if a person likes to play piano duets or tennis, they are apt to be rewarded by those who make it possible for them to do so, and at the same time they are apt to reward their partner (Newcomb, 1956).

Along the same lines, the *Uncertainty Reduction Theory* (URT) (Berger & Calabrese, 1975) states that when two strangers interact for the first time, they have a cognitive need to gain adequate information about one another and their behavior to serve as a guide for decisions on continuing or terminating future interactions. At the beginning, people face an ambiguity about outcomes and reactions in conversation because uncertainty levels about each other are high. In order to assess possible costs/risks and benefits of the relationship, they aim to reduce uncertainty through explanation (retroactive attribution) and prediction (proactive attribution).

Extending on URT and complementing SET, the *Predicted Outcome Value Theory* (POV) of communication (M. Sunnafrank, 1986) posits that people attempt to determine the benefits of interpersonal relationships by predicting the value of future outcomes whether negative or positive.

Attraction increases as the predicted outcome value increases and prediction of positive future outcomes leads to future interactions. Based on this we put forward that reciprocal benefits and rewards from the relationship are important relational determinants of chance encounter.

2.2.4 Mere Exposure Theory

Based on the *Mere Exposure Theory* (Zajonc, 1968), people tend to develop a preference for things that are more familiar to them. Therefore people who are physically close and see each other regularly have a better chance of being attracted to each other. Other researchers found that not merely the physical proximity but the resulting opportunity to interact increases attraction (Insko & Wilson, 1977) and that proximity simply provides the occasion for the discovery of common attitudes (Newcomb, 1956). Prior work pointed out that people often interact with similar others because they simply have more opportunities to meet similar others than to meet those that are dissimilar (Fischer, 1977; Kalmijn & Flap, 2001; Marsden, 1990). Geographic location, a person's physical position in time and space, may promote or inhibit chance encounters due to limited or increased opportunities to communicate face-to-face (Sproull & Kiesler, 1986). The probability of a face-to-face contact between two people decreases exponentially as the physical distance increases because distance increases effort (Festinger, Back, & Schachter, 1950; Sykes, 1983).

Familiar strangers are people who see each other regularly but do not directly interact (Milgram, 1977). Paulos & Goodman (2004) found that if familiar strangers meet in an unfamiliar setting, for example while travelling, they are more likely to introduce themselves than would perfect strangers, as they have a background of shared experiences.

In summary, physical distance between people is an important factor affecting chance encounters.

2.3 Social Determinants of Chance Encounters

While similarity and proximity definitely play a significant role in social tie formation, researchers also argued that friendship cannot be understood from individualist or dyadic perspectives alone, but is significantly influenced by the environment in which it is generated (Adams & Allan, 1998). Chance encounters are reliant on an environment where people are willing and able to make new acquaintances. We discuss social determinants of chance encounters based on the current environment of a person as understood in a social sense, such as their current place, social norms, crowding and population density as well as time / synchronicity.

2.3.1 Place

While physical location, like GPS coordinates, does not have any substantial meaning to people, *place* refers to how people are aware of a certain location (Tuan, 1977). A place is “a space, which is *invested with understandings* of behavioral appropriateness, cultural expectations” (Harrison & Dourish, 1996). Places act as “social” filters and different types of places attract certain people (Levine, 2003). Just like individuals, they have their own personalities, which make these places feel familiar and safe for some people but not others. Certain place characteristics may serve as a determinant for likeminded strangers to have opportunities to get to know one another (Verbrugge, 1977). Levine (2003) found that it is less the nature of the person that predicts helping a stranger during a chance encounter, but the characteristics of the local environment. Jones et al. (2004) explored the places in which people want to know about other people. The places where individuals expressed an interest in this included airports, train stations, pubs, and diners. Commonalities between these places included that they were either designed for socializing or places where people have long waiting periods.

2.3.2 Social Norms

Opportunities for chance encounters are further shaped and constrained by various institutionally organized arrangements of a place (e.g., work, school, family, or neighborhoods) and associated social norms and conventions, as well as socio-structural conditions at the place. Goffman (1966) defined so-called "open regions" as physically bounded places where any two persons, acquainted or not, have the right (or are expected) to socialize with strangers. In American society, bars and cocktail lounges, vacation resorts, and other highly bounded settings tend to be defined as open regions. Furthermore, social parties and gatherings in private homes become open regions where it is socially acceptable and even encouraged to initiate conversations with self-introductions. This is subject to cultural differences as well as societal progress. Shimanoff's rules of communication (1980) further outline culturally defined situations in which persons located near each other are expected to be sociable even though they are strangers, e.g., parties or dinners; classes; work, church, or recreation groups; and at summer camps and conferences. In such situations, persons are expected to talk to strangers. Jones et al. (2004) found that the desire for information about other people nearby related to the expected behaviors for a place. Moreover, literature points out that people are most likely to start new relationships after entering a new social context (e.g., starting a new job or university) (Feld & Carter, 1998; Mollenhorst et al., 2014).

2.3.3 Crowding and Population Density

Crowding and the resulting closeness to strangers is another aspect that influences the opportunity for chance encounters. Liben-Nowell & Kleinberg (2007) argue that in addition to the absolute value of geographic distance, population density has to be considered to model friendships. Jones et al. (2004) found that when there are large numbers of unknown people nearby, people want to know about them. Freedman's *Density-Intensity Model* (1975) describes that the feeling of crowding based upon an individual's perception and explains that crowding is neither good nor bad, but that with increasing density of people nearby, the intensity of moods and behavior increase. Based on that, Sykes (1983) suggests that people may experience crowding as unpleasant and potentially threatening and in order to chase away the experienced discomfort they may start small talk and pleasantries.

On the other hand, *urban overload* and population density might decrease the occurrence of chance encounters (Levine, 2003; Milgram, 1977). People in large cities tend to keep to themselves more to lessen stimuli. Levine (2003) explored local as well as environmental variations in people's willingness to help a stranger during a chance encounter and found that people in more crowded cities were much less likely to take the time to help. In his words, "*squeezing too many people into too small a space leads, paradoxically enough, to alienation, anonymity and social isolation*" (Levine, 2003).

2.3.4 Time Dependency and Elasticity of Synchronicity

Chance encounters are time-dependent, as all communication is temporally sensitive. Naturally, in-person chance encounters are synchronous, as the communication occurs face-to-face and real-time. However, Bandura (Bandura, 1982) already discussed in 1982 that using print, audio, and audio-video media as communication modes can exceed the limitations of time and place and connect unacquainted and widely dispersed people. Today, communication technology stretches the edges of the synchronicity continuum (Newhagen & Rafaeli, 1996). While synchronous tools enable real-time communication and collaboration in a "same time-different place" mode, asynchronous tools enable communication and collaboration over a period of time through a "different time-different place" mode. Therefore, online chance encounters are not determined by time or place, while face-to-face encounters are reliant on same time-same place situations.

2.4 Personal Determinants of Chance Encounters

Chance encounters are further reliant on personal determinants, such as people's current openness or mood to meet someone, ability and willingness to engage in a chance encounter based on potential engagement in another task, and their belief in a successful outcome. We discuss personal determinants in terms of personality and state of mind, Cognitive Load Theory, as well as Self-Efficacy, Attribution Theory and Pluralistic Ignorance.

2.4.1 State of Mind and Personality

A famous quote from scientist Louis Pasteur (1822-1895) says, *"Chance favors the prepared mind."* Wiseman found that being lucky means not only being in the right place at the right time, but also being in the *right state of mind*. He argued that adopting a relaxed attitude to life and being open to new experiences influences luck and opportunities people have (Wiseman, 2003). This also applies to chance encounters, as they require people to be open and willing to engage with another person. Along the same line, Openness-to-Experience (i.e., openness) is one of the domains, which is used to describe human personality in the Five Factor Model (McCrae & Costa, 1987; McCrae & John, 1992). Individuals who demonstrate high Openness-to-Experience have broad interests and seek novelty, with low ratings linked to preferring familiarity and convention. Bandura (1982) describes *psychological closedness,* a mental state where people are not open to be influenced by others because of strong existing authoritarian belief systems, as an inhibiting factor of chance encounters being fruitful.

Moreover, it was found that loneliness tends to increase openness and likelihood of contact initiation while shyness decreases contact initiation (Berger & Bell, 1988). Other personality dispositions that are likely to influence how people experience chance encounters are extroversion and sociability. Extraverts are typically adventurous, sociable and talkative, whereas introverts are typically quiet and shy (Costa & McCrae, 1992). Sociability describes the tendency to enjoy conversation, social interaction and being the center of attention. Individuals who score low on measures of Sociability prefer solitary activities and will not actively seek conversation (Ashton & Lee, 2009).

While it was originally believed that personality was more or less static and that personality traits usually do not change much over time, research now suggests that people can adopt different levels of a personality dimension based on the social situations and time of day (Fleeson, 2001; Funder, 2012). On the other side, mental states are very dynamic and influenced by context, as well as by internal changes. For example, feelings may change cognition and cognition may change actions.

2.4.2 Cognitive Load Theory

The occurrence of chance encounters might further be influenced by people's cognitive load, i.e., how busy or engaged in another task they are. Based on the *Cognitive Load Theory* (Sweller, Ayres, & Kalyuga, 2011), people have limited mental processing resources and attention is selectively concentrated on one aspect of the environment while ignoring other things (i.e., allocating processing resources). If people's attention is already differently allocated, i.e., through a person's current or anticipated engagement in an activity or task, this might inhibit chance encounters. Enforcing this theory, Jones et al. (2004) found the desire for information about other people nearby related to people's current activity and future plans. For example, when people have long waiting periods or need to pass time they tend to be interested in people nearby. Similarly, *cognitive engagement* has been defined in educational research as the extent to which students are willing and able to take on the task at hand (Rotgans & Schmidt, 2011).

2.4.3 Self-Efficacy, Attribution Theory and Pluralistic Ignorance

Pluralistic ignorance resulting from low self-efficacy and misattribution is another factor that may inhibit chance encounters. *Self-efficacy* is belief in one's ability to succeed in a specific situation, such as completing a task or reaching a goal (Bandura, 2010). People who think they can perform well on a task do better than those who think they will fail (Bandura, 2010; Gist & Mitchell, 1992). This strongly influences people's behavior, e.g., the choices a person is most likely to make: People generally stay away from actions where self-efficacy is low, but perform actions where self-efficacy is high. In regards to chance encounters, self-efficacy might determine if people initiate contact with a stranger.

Attribution Theory describes how people use information to explain other people's behavior and events as well as how this interacts with self-perception (Fiske & Taylor, 1991). In social psychology, *pluralistic ignorance* is a situation where a majority of group members privately reject a norm, but assume incorrectly that most others accept it, or vice versa (Katz, Jenness, & Allport, 1931). It was found that pluralistic ignorance can inhibit people making the first move in contact initiation because they justify their own inaction in terms of their fear of being rejected, while they attribute a potential partner's inaction to a lack of interest (Vorauer & Ratner, 1996).

2.5 Impact of Chance Encounters

Our overarching motivation of mediating chance encounters stems from the fact that chance encounters can play a prominent role in shaping the course of people's life paths (Bandura, 1982). Formation of valuable social ties and creation of new social capital are amongst the most valuable outcomes of chance encounters, as discussed in the following sections.

2.5.1 Formation of New Social Ties

Chance encounters lay the base for the formation of new social ties. Social ties are defined as information-carrying connections between people that may vary in strength. The strength of a social tie is defined by the amount of time spent in the relationship, the emotional intensity, the intimacy (or mutual confiding), and the reciprocal services (Granovetter, 1973). Other research suggests additional dimensions of tie strength, such as communication reciprocity (Friedkin, 1980), possessing at least one mutual friend (Shi, Adamic, & Strauss, 2007), recency of communication (Lin, Dayton, & Greenwald,

1978) and interaction frequency (Gilbert, Karahalios, & Sandvig, 2008). Strong social ties are typically close friends and family, while weak social ties are loose acquaintances, such as a friend-of-a-friend, who may provide useful information or new perspectives for one another but usually not emotional support (Granovetter, 1973). Weak ties are characterized by absent or infrequent contact, lack of emotional closeness, and no history of reciprocal services. Furthermore, absent social ties (also known as *familiar strangers* (Milgram, 1977)) are relationships without substantial significance such as nodding to someone who lives on the same street. Granovetter (1973) suggests that weak ties could offer an advantage over strong ties in obtaining useful, non-redundant information because strong ties are usually built with similar people who are likely to know the same things and are unlikely to know dissimilar things. In addition, it was found that people have a basic psychological need to feel connected to others ("belongingness hypothesis" (Baumeister & Leary, 1995)) and that both weak and strong social ties help people to attain self-confidence and a sense of self-direction (Bandura, 1982).

2.5.2 Community and Social Capital

Social ties are the basic ingredients of communities. A community is defined as a tight and more cohesive social entity usually characterized by common beliefs, a shared place, direct sense of loyalty between individuals and a "unity of will" (Tönnies, 1887). *Social capital* is a term used to describe the productive benefits that come from communities (Dekker & Uslander, 2006). There are numerous definitions for *social capital* due to its complex and multi-dimensional nature across multiple fields (Adler & Kwon, 2002). Putnam defines *social capital* as the "features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit" (Putnam, 1995). Social capital emerges from a diverse network of both strong and weak ties and affects flow of information, influence, and solidarity (Sander, 2002), supports strong norms of generalized reciprocity (Putnam, 1995), and enables people to act collectively (Woolcock & Narayan, 2000). Putnam (1995) distinguishes between *bridging* and *bonding* social capital. Strong social ties are the basis of bonding social capital, such as family and close friends (Granovetter, 1973). Bridging social capital on the other hand relies on weak ties that link small groups of strong ties (e.g., two or three best friends) in larger groupings. Overall, social capital comes with impressive payoffs as it makes a community more cohesive and provides a greater ability for acting collectively (Granovetter, 1973), to confront poverty and vulnerability (Moser, 1998; Narayan-Parker, 1999) and allows dilemmas of collective action to be resolved (Putnam, 1995).

2.6 Summary

This chapter examined dynamics of chance encounters. Chance encounters were defined as events where paths of strangers cross and their unplanned interaction turns out to be of value to either (or both) parties. We explored the notion of chance, luck as well as opportunity in regards to chance encounters and learned that chance encounters often seem random serendipitous incidents. In order to gain a deeper understanding of how to predict chance encounters we examined their potential determinants, such as the relationship between people (*relational determinants*) as well as how their current social environment (*social determinants*) and state of mind (*personal determinants)* play important roles in serendipitous meetings between people. Discussed relational determinants include social identity, similarity or complementarity between people, expected outcome of an encounter, as well as physical and temporal proximity. Furthermore, we learned that social determinants, such as place characteristics, social norms, and density of people nearby might mediate or inhibit chance encounters. Personal determinants affecting chance encounters include personality and mental state, people's engagement in an activity (i.e., busyness), and pluralistic ignorance based on self-efficacy and attribution theory. At the end of this chapter, the impact of chance encounters is discussed in terms of potentially formed social ties and creation of new social capital.

From this review, we learned that predicting the occurrence of chance encounters can only be done in a very general way. Relational, social and personal determinants make some types of intersects more probable than others. However, further research is needed to understand the interplay of these and other determinants from a system building perspective in order to mediate chance encounters. The next chapter focuses on technological concepts that potentially can be used to mediate chance encounters.

CHAPTER 3

COMPUTER-MEDIATED CHANCE ENCOUNTERS

In previous chapters, we investigated dynamics of chance encounters and gained a deeper understanding of different factors affecting their occurrence. In this chapter, we are turning our attention to technology and how to design for mediating chance encounters. In order to translate previously discussed determinants into system design, this chapter reviews relevant technological concepts that could be used to capture, model and utilize relational, social, and personal determinants computationally. Notions of context-aware computing and recommender systems are introduced and reviewed in terms of their potential to support chance encounters. This will provide us with a better understanding about how chance encounters could be mediated using technology.

3.1 Context-Aware Computing

As noted previously, chance encounters are affected by relational, social and personal determinants. In order to mediate chance encounters, systems would need an in-depth understanding of these determinants. *Context-aware computing* is a mobile computing paradigm that aims at understanding the user's current context and treating it as an implicit input to automatically react to the user's dynamic environment (Abowd et al., 1999; Dey, 2001). Context-awareness originated as a term from ubiquitous / pervasive computing, which is related to the idea of *calm technology* (Weiser, 1991) referring to technology being ubiquitous in everyday life and performing computations hidden from the user's attention. Similarly, context-aware applications run in the background without a lot of interaction with the user and are deeply embedded in the physical instead of a virtual environment. Considering that people are often not sitting at their desktop computers but are instead immersed in other activities, context-aware applications aim at automatically sensing the situation in which they are immersed and adjusting their behavior appropriately (Abowd et al., 1999; Wellman, 2000). Mobile phones have become ubiquitous connecting people anytime and anywhere, and are able to collect increasing amounts of information using various sensors, such as user location, user movement, environmental noise, temperature, and people nearby (Abowd et al., 1999; Ballagas et al. , 2006; Beale, 2005; Borcea et al., 2007; Eagle & Pentland, 2006). In the following sections, we will review various definitions of context as well as examples of context-aware systems before we identify the components of context that are relevant for computer-mediated chance encounters.

3.1.1 Defining Context

Even though most people implicitly understand what context is, it is hard to elucidate what the term "context" encompasses. In the context-aware computing literature, no unified definition of context exists and numerous researchers define "context" in different ways. According to the Merriam-Webster dictionary, synonyms for "context" include "environment", "setting" or "situation". In the work that introduced the concept of "context-awareness", Schilit and Theimer (1994) refer to context as "*location, identities of nearby people and objects, and changes to those objects*". They claim that the important aspects of context are: where you are, who you are with, and what resources are nearby. Brown et al. (1997) list "*location, identities of the people around the user, the time of day, season, temperature, etc.*" as contextual information. Ryan et al. (1997) simply define context as the user's "*location, environment, identity, and time,*" while Abowd et al. (1999) extend this definition by specifying context as "*any information that can be used to characterize the situation of an entity where an entity could be a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves*". In addition to current context, this may also include historical context data to establish trends and predict future context values (Baldauf et al., 2007). Furthermore, context may include an individual's calendar appointments, blood pressure, or current activities, traffic conditions, airline schedules, the weather, or the set of people in the same room (Cohen et al., 2004).

However, not all kinds of contextual information might be relevant or useful for the system's purposes. Defining what information is *contextually relevant* to the user and his/her interaction with the application is one of the biggest challenges in context-aware computing. Dourish (2004) argues that context should be understood as a *relational property* between objects or activities defining whether something is contextually relevant to some particular activity. Availability of vast amounts of contextual information in mobile systems along with the lack of uniform methods to define, acquire and process context has pushed forward new challenges in the community. For an operational context-aware system, it is crucial to have an effective model for collecting, storing, and processing context data.

3.1.2 Collecting Contextual Data: An Overview of Mobile Sensors

In order to collect contextual data, a multitude of sensors can be leveraged. While early research in mobile sensing required specialized mobile devices, such as the Mobile Sensing Platform [MSP] (Choudhury et al., 2008), the widespread adoption of mobile phones with cheap and powerful built-in sensors allows rich contextual data collection (Lane et al., 2010). The most commonly used contextual data point is user location. The Global Positioning System (GPS) was developed by the U.S. Department of Defense and was first included in cellphones in the late 1990s. It allows the phone to localize itself, enables location-based applications such as local search, mobile social networks, and navigation (Dana, 1997). Additionally, technologies like Bluetooth, Wi-Fi and NFC all allow wireless communication and data exchange between digital devices like smartphones. Bluetooth beacons can capture a very precise indoor location in a specific area (Borenstein, Everett, Feng, & Wehe, 1997; Want, Hopper, Falcão, & Gibbons, 1992). Cell-ID and Wi-Fi can each provide a clue to user location. Detecting whether the user has entered a certain area can be done with short-range wireless systems, such as RFID (radio-frequency identification) with a badge. Near field communication, or NFC for short, is an offshoot of RFID with the exception that NFC is designed for use by devices within close proximity to each other[6]. It utilizes electromagnetic radio fields while technologies such as Bluetooth and Wi-Fi focus on radio transmissions instead.

Moreover, today's mobile smartphones have sensors that can measure motion, orientation, and various environmental conditions (Android Developer Guide, n.d.; Shoaib, Scholten, & Havinga, 2013). These sensors are capable of providing raw data with high precision and accuracy, and are useful to infer implicit information about a user's current context. Motion sensors, such as accelerometers, gravity sensors, gyroscopes, and rotational vector sensors, can measure acceleration forces and rotational forces along three axes. Distinct patterns within the accelerometer data can be exploited to automatically recognize different activities (e.g., running, walking, standing) (Miluzzo, Lane, Eisenman, & Campbell, 2007)

Environmental sensors include barometers, photometers, and thermometers and can measure ambient air temperature and pressure, illumination, and humidity. Position sensors, such as orientation sensors and magnetometers, measure the physical position of a device. The sensors represent an extension of location, providing the phone with increased awareness of its position in relation to the physical world, enhancing location-based applications. On top of this, there are proximity sensors for recognizing when the user moves the phone up to his or her face during a call, ambient light sensors for boosting brightness levels in dark environments, and fingerprint scanners that can measure users' heart rates, and check their current temperature.

This shows that there is a multitude of contextual information available on mobile phones. The biggest challenge in context-aware computing is to identify which information is relevant to the user at a given point in time, and how to process contextual data to adapt the system's behavior in a meaningful way.

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[6] http://www.nearfieldcommunication.org/ (accessed Jan. 2016)

3.1.3 Levels of Interactivity in Context-Aware Systems

In 1997, Ben Shneiderman and Pattie Maes started a discussion that is still relevant to today's system designers, as well as to our work: Direct manipulation versus interface agents (Shneiderman & Maes, 1997). The term *direct manipulation* was introduced by Ben Shneiderman in 1982 within the context of office applications and the desktop metaphor, and refers to computers only responding when a person gives commands from a keyboard, mouse or touch screen (Shneiderman, 1982). The computer is merely a passive entity waiting to execute specific, highly detailed instructions. Pattie Maes, on the other hand, argues for *intelligent agents*, which "know" users' interests and can act autonomously on their behalf. Instead of exercising complete control (and taking responsibility for every move the computer makes), people will be engaged in a cooperative process in which both human and computer agents initiate communication, monitor events and perform tasks to meet a user's goals.

Along the same lines, context-aware systems can implement different levels of interactivity (Barkhuus & Dey, 2003a; G. Chen & Kotz, 2000). *Personalization* is where applications let the user specify his own settings for how the application should behave in a given situation; *passive context-awareness* presents updated context or sensor information to the user but lets the user decide how to change the application behavior, whereas *active context-awareness* autonomously changes the application behavior according to the sensed information. Research has shown that users prefer active and passive context-aware features over personalization-oriented applications in most cases and are willing to accept a large degree of autonomy from applications as long as the application's usefulness is greater than the cost of limited control (Barkhuus & Dey, 2003a). Along the same lines, prior work has explored whether information should be pushed towards the user or the user should be left to pull the information on his own in context-aware systems (Cheverst, Mitchell, & Davies, 2001), whereas others argue that only push-based applications should be called context-aware (Erickson, 2002).

3.1.4 Examples of Context-Aware Systems

The *Active Badge Location System* (Want et al., 1992) could be considered as one of the first context-aware applications, using infrared technology to forward phone calls to a telephone close to the user based on a their current location. In the late 1990s, several location-aware tour guides were developed to provide information depending on the user's current location (Abowd et al., 1996; Cheverst, Davies, Mitchell, & Friday, 2000; Sumi et al., 1998). While location information is by far the most commonly used aspect of context, efforts to use additional context information have been made to build more adaptive, useful and user-friendly systems (Baldauf et al., 2007). For example, the concept of P3 systems (people-to-people-to-places) proposed to consider relationships between users as well as users' relationships to geographical places in context-aware systems (Jones et al., 2004). Further examples of context-aware applications include systems that advise a driver to take a particular route based on traffic conditions (Santa & Gómez-Skarmeta, 2009), advise a nurse to attend to a particular patient based on the medical telemetry being received from all patients on a ward (Bardram, 2004; Munoz, Rodriguez, Favela, Martinez-Garcia, & Gonzalez, 2003), and recommend a movie based on a user's current mood (Y. Shi, Larson, & Hanjalic, 2010).

3.2 Recommender Systems

Concepts of recommender systems can also be useful to mediate chance encounters between people. Recommender systems recommend previously unseen items to users based on estimated ratings for these items (Adomavicius & Tuzhilin, 2005; Groh, Birnkammerer, & Köllhofer, 2012) and in this way promise to help users dealing with overwhelming amounts of information by providing personalized suggestions (Resnick & Varian, 1997). Traditional recommender system items typically encompass products, services, media items (films, music, etc.), information items (news, documents), and collections of information items (web pages, portals) (Groh et al., 2012). However, the object of recommendation could also be a *person,* which is of particular interest to this work.

Recommender systems can be classified by the method of recommendation: content-based or collaborative filtering (Groh et al., 2012). Both approaches have been combined to improve the recommendation method (i.e., hybrid methods) (Konstas et al., 2009). In the following sections we will discuss these two methods in more detail, as well as challenges that arise from them and how hybrid methods address them. Further, we look at context-aware recommendation systems and social recommender systems, which both seem promising approaches for computer-mediated chance encounters.

3.2.1 Content-based Recommendation Methods

In content-based recommendations, the user is recommended items similar to the ones the user preferred in the past (Adomavicius & Tuzhilin, 2005; Lops, Gemmis, & Semeraro, 2011). Content-based recommender systems build a model or profile of user interests based on features of objects rated by that user and aim to identify commonalities among items a user has rated highly in the past (e.g., for movies: specific actors, directors, genres, subject matter, etc.) (Adomavicius & Tuzhilin, 2005). Keyword weights to identify relevant information are typically calculated using the *term frequency/inverse document frequency* (TF-IDF) measure. It is based on the assumption that the frequency of a word in a document compared to the frequency of that word in the set of all documents is an indicator of the importance of that word (Robertson, 2004). The recommendation process consists of matching the attributes of the user-profile and the attributes of a recommendation item to recommend items with a high degree of similarity to the user's preferences (Lops et al., 2011).

3.2.2 Collaborative Filtering

The other widely used technique in recommender systems is collaborative filtering (CF) (Cohen et al., 2004). Collaborative recommendations are based on the idea that personal tastes are correlated: If Alice and Bob both like X and Alice likes Y then Bob is more likely to like Y, especially (perhaps) if Bob knows Alice (Adomavicius & Tuzhilin, 2005). Collaborative recommender systems aim to find the "peers" of users, i.e., people with similar tastes and preferences, and then recommend items that have been liked by those "peers" in the past. The taste-similarity between two users is computed based on their ratings of items that both users have rated. The two most popular approaches are correlation- and cosine-based similarity calculations (Konstas et al., 2009). While in content-based recommender systems the similarity between vectors of TF-IDF weights is used, in collaborative systems the similarity between vectors of the actual user-specified ratings is measured. An interesting approach here is *inverse user frequency transformation* based on the idea is that 'rare' items are more useful in deciding how similar two users' tastes are (Symeonidis et al., 2007). In calculations, preference values for items for which only some users have expressed a preference are increased, and preference values for items for which several users have expressed a preference are decreased. Collaborative filtering is for example used in Amazon's book recommendation system (Linden et al., 2003).

3.2.3 Challenges in Recommender Systems

These two methods in recommender systems are prone to several open challenges. For example, the content-based approach can suffer from *over-specialization*, when the user is limited to being recommended items similar to those already rated (e.g., a person with no experience with Greek cuisine would never receive a recommendation for even the greatest Greek restaurant in town) (Adomavicius & Tuzhilin, 2005). This has been addressed by introducing some randomness to increase the diversity of recommendations. Ideally, the user should be presented with a range of options and not with a homogeneous set of alternatives. The *new user problem* is another problem content-based methods experience. Before a recommender system can really know a user's preferences, the user has to rate enough items. Therefore, a new user, having very few ratings, would not be able to get accurate recommendations (Adomavicius & Tuzhilin, 2005). Furthermore, in any recommender system, *sparsity of ratings* might become a challenge. It is essential that systems can make effective prediction based on ratings from a small number of examples. Also, the success of the collaborative recommender system relies on the existence of a *critical mass of users*.

3.2.4 Hybrid Methods

Several recommendation systems aim at addressing previously discussed challenges by using hybrid approaches that combine collaborative and content-based methods (Balabanović & Shoham, 1997). The following methods merging collaborative and content-based methods into a hybrid recommender system have been studied: employ collaborative and content-based methods separately and aggregate their predictions; add some content-based characteristics into a collaborative approach or vice versa; or implement a general unifying model that includes both content-based and collaborative features (Adomavicius & Tuzhilin, 2005; Balabanović & Shoham, 1997).

3.2.5 Context-Aware Recommender Systems

Context-awareness can be helpful to adapt current user needs and provide timely and relevant recommendations. *Context-aware recommender systems* (CARS) incorporate contextual information into the recommender system such as location and time in order to get more personalized recommendations (Adomavicius & Tuzhilin, 2011; Yu et al., 2006). Example applications of context-aware recommender systems include recommending movies for a specific time or a specific emotional status (Y. Shi et al., 2010); recommending websites based on social, historic, task, collection, and user interaction (White, Bailey, & Chen, 2009); or using temporal context in a travel recommender system to provide different recommendations in the winter and in the summer (Adomavicius & Tuzhilin, 2011). Moreover, *Magitti* is an activity-centered mobile leisure-time guide that recommends nearby venues for pursuing activities in a timely and personally relevant manner (Bellotti et al., 2008). The application infers user activity from context and patterns of user behavior and automatically generates recommendations.

3.2.6 Social Recommender and Social Matching Systems

Social recommender systems are particularly relevant to this work, since social entities (e.g., persons or groups of persons) are used in certain aspects and components of traditional recommenders (Groh et al., 2012). This might mean including social entities into the traditional collaborative filtering method by using friends on a social networking platform (e.g., Facebook) or using the social situation a user is currently immersed in to predict a preferred product (Groh et al., 2012). However, this work is mostly concerned with social recommender systems where the object of recommendation itself may be a social entity, i.e., a person. Recommendation systems that recommend people to people are known as *social matching systems* (Terveen & McDonald, 2005). Social matching systems are very promising to support chance encounters and will be discussed in more depth in the next chapter.

3.3 Summary

In this chapter, we discussed technological concepts, such as context-awareness and recommendation systems, that potentially could be used to mediate chance encounters. We previously learned that context plays an important role in chance encounters. Hence, context-aware recommender systems are especially interesting for this work, as they consider contextual information in the recommendation process. Moreover, social recommender systems that include social entities in the recommendation were identified as relevant to this work, as they potentially can recommend people-to-people. As a next step to broaden our understanding of potential design solutions to mediating chance encounters, the next chapter delves deeper into this concept, also known as *social matching*.

CHAPTER 4

SOCIAL MATCHING SYSTEMS

The previous chapter outlined how notions of context-aware computing and recommender systems could be used to mediate chance encounters. In this chapter, social matching systems (a special case of social recommender systems) are reviewed in more detail with regards to their potential in mediating chance encounters.

4.1 Defining Social Matching

Social matching systems recommend people to people (Terveen & McDonald, 2005). Recommending people to people is very different in nature than recommending products, music or movies to users because of the complex underlying social processes when people are both the subject and objects of the recommendation. The most popular types of social matching systems are online dating sites such as Match.com[7] or eHarmony[8]. However, social matching applications are beginning to support a broader range of social needs, e.g., means for professional collaboration (CoFoundersLab[9]) and professional networking (LinkedIn's "*People You May Know*" feature[10]).

Matchmaking is generally *two-sided or reciprocal,* i.e., both users are recommended to each other, which is why systems have also been referred to a *reciprocal recommender systems* (Pizzato, Rej, & Chung, 2010). The challenge here is that just because one person is looking for a specific type of person does not mean that persons who fit this requirement will be interested in that person in return. A simpler form of matchmaking is *one-sided,* i.e., where only one user is recommended to the other one, but not vice versa (e.g., expert recommender systems). Moreover, recommending

[7] http://www.match.com (accessed Jan. 2016)
[8] http://www.eHarmony.com (accessed Jan. 2016)
[9] http://www.cofounderslab.com (accessed Jan. 2016)
[10] http://www.linkedin.com (accessed Jan. 2016)

unfamiliar yet interesting people is different from recommendation of already known people (Guy, 2012; Guy et al., 2011). The goal of mediating chance encounters is to reciprocally recommend unknown but interesting or relevant people when the opportunity arises.

4.2 The Social Matching Process

The social matching process has been outlined in (Terveen & McDonald, 2005) consisting of the following four steps: 1) collect and model user data (*modeling*), 2) calculate affinities to identify potential matches (*matching*), 3) notifying the user of matches (*introducing*) and 4) mediating the introduction process (*interacting*). To more clearly relate these steps as they relate to our research, we split the social matching process in two parts (Figure 4.1): *Affinity Modeling* and *User Interaction*. Affinity modeling is the process of gathering data from users to build profiles that enable the system to compute social matches. User interaction includes the exchanges between the system and the user to send a match notification and facilitate the introduction and further communication between matched users. Note that the results of the user interaction (success or fail) should ideally feed back to the affinity modeling, causing updates to its calculations. We will discuss these steps in more detail in the following sections.

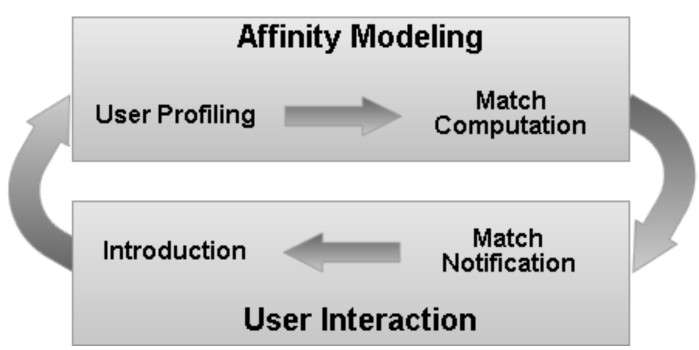

Figure 4.1 Updated social matching process.

4.3 Step 1: User Profiling

A social matching system needs to collect information about its users, i.e., their interests, demographics and other personal features, social network information and ideally as noted earlier also contextual information. This information is used to build an extensive user profile as a base for match computation. Profiles can be built using different types of user information: (1) *explicit*, i.e., self-reported by users, and (2) *implicit*, i.e., inferred by the system.

4.3.1 Explicit User Profiling

The most straightforward way to collect user information is to ask users to input the information manually. In order to collect self-reported explicit personal user information, social computing applications usually provide users with profile management user interfaces (UIs). These interfaces are usually structured for the kind of data a user can enter (e.g., name, interests, contact information, demographics and a profile picture) and implement basic access control tools that allow users to directly control other people's access to their information. In particular, online dating sites such as Match.com[11], or eHarmony[12] require users fill out long questionnaires and personality tests to do psychological profiling. Figure 4.2 shows public profiles of users on different social matching platforms.

[11] http://www.match.com (accessed Jan. 2016)
[12] http://www.eharmony.com (accessed Jan 2016)

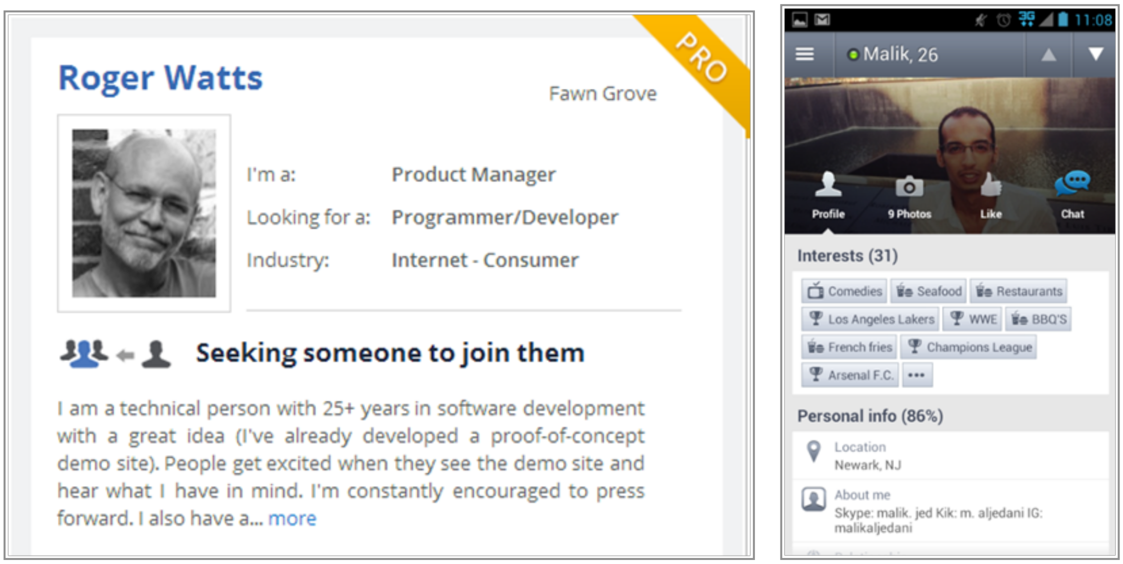

Figure 4.2 Examples of public user profiles on different social matching platforms: CoFoundersLab (left) and Skout (right).

Source: CoFoundersLab [http://www.cofounderslab.com, accessed Jan. 2016] (left), Skout [http://www.skout.com, accessed Jan. 2016] (right)

4.3.2 Implicit User Profiling

While self-reported user profiling usually results in very specific user data, filling out long questionnaires and profiles puts a lot of burden on users and might be intrusive and cumbersome. Therefore, often only limited explicit information is available.

In order to not only rely on self-reported data and get more extensive user models, systems could apply data mining, machine learning and other statistical inference techniques to infer additional user information that has not been explicitly revealed (Adomavicius & Tuzhilin, 2011). *Social inferences* in social computing refer to the process of inferring previously undisclosed information about a user by linking explicitly revealed *personal information* with *context information* and *community information* about the environment a user is currently traversing (Mayer, Schuler, & Jones, 2012; Motahari et al., 2011; Motahari et al., 2009).

Systems can infer implicit information, for example from keyword mining from users' personal files and folders or from activity in social media, such as bookmarking web pages, use of specific tags, and membership in communities (Guy et al., 2011).

Along the same lines, some recommender systems use proxies to estimate ratings in order to minimize required effort from the user. For example, the amount of time a user spends reading a newsgroup article has been used in prior recommender systems research as a proxy of the article's rating given by this user (Adomavicius & Tuzhilin, 2005).

It has been shown that systems can infer relationship characteristics from mobile phone data (Eagle, Pentland, & Lazer, 2009). Previous research has detected proximity patterns and correlated them with relationship types to make inferences about a user's social network (Eagle & Pentland, 2005). Information about the existing social network of a user (e.g., tie strengths and tie labels like "friend", "colleague") can be used to infer additional interests (Wen & Lin, 2011). Moreover, systems could infer user interests based on the current activity or record of past activity of the user (White et al., 2009).

Previous work has also proposed approaches to infer *social situations* based on the set of persons participating in a social situation, the time interval of the situation, the spatial reference of the social situation, and the set of keywords describing the semantics of the social situation (Groh & Lehmann, 2011). Moreover, the concept of *situated social context* (Endler et al., 2011) has been proposed to infer the set of people that share some common spatial-temporal relationship with the individual, which turns them into potential peers for interaction in a specific situation. In addition, it has been shown that systems are able to infer a detailed understanding of social situations and discover ad-hoc or semi-permanent social groups as well as predict the probability of contact between two users by using proximity information (Mardenfeld et al., 2010; Miluzzo et al., 2007).

While social inferences mitigate the workload of filling out long questionnaires and profiles and providing ratings, they can also lead to privacy invasions at other times. A fine balance of minimizing intrusiveness while maintaining certain levels of privacy needs to be the aim of system designers. In the following section privacy considerations are discussed.

4.3.3 Privacy

The collection of explicit personal and contextual information as well as inferring implicit information requires a thorough understanding of users' privacy concerns. Privacy is a multi-faceted and complex topic and there are numerous definitions of privacy. One perspective on privacy is provided by Fried (Fried, 1968) defining it as the "*control over knowledge about oneself*". In other words, privacy is a person's ability to exclude others from accessing their personal information and, more specifically, the ability to determine when, how, and to what extent he or she will release personal information. Parker (1973) defines privacy based on who can "sense" us: *"[Privacy is…] control over when and by whom the various parts of us can be sensed by others."* The term "sensed" can be understood as being seen, heard, touched, smelled, or tasted - either physically or digitally. The expression "parts of us" can refer to parts of our bodies, our voices, and the products of our bodies. This definition will be adopted for this work because it is sensitive to how location-aware mobile devices may violate the perceived right to privacy.

Privacy concerns can be reduced if systems allow users to see and remove particular collected data or to stop the logging entirely and to decide what information they want to share (Barkhuus & Dey, 2003b; Eagle & Pentland, 2006). However, as Cas (2005) notes, privacy in pervasive computing environments may be a contradiction in terms, as the functioning of many applications requires the sensing of users as well as the disclosure of personal location-based information.

Although people are concerned about their privacy, they are often willing to provide personal information to enable beneficial software services (Barkhuus & Dey, 2003b). The calculus perspective of information privacy takes into account the dynamic and social aspect of privacy and interprets the individual's privacy interests as an exchange where individuals disclose their personal information in return for certain benefits (Li, Sarathy, & Heng, 2010).

4.4 Step 2: Match Computation

The process of computing matches between user profiles consists of determining compatible pairs of users based on certain predefined match criteria (i.e., the match algorithm). As discussed earlier, user profiles might be explicit (from self-reported data) or inferred (from implicit data). What kinds of user data and match criteria are used may vary depending on the system's specified purpose and user goals on the platform, such as finding a date, new friends, collaborators, or an expert. The most sophisticated matching algorithms currently are those for online dating aiming to find *the* perfect match for a lifetime (Hitsch et al., 2006; Hitsch et al., 2010). However, the aim of this work is not to match romantic lifetime partners but instead to understand how context can be incorporated in the match computation to support spontaneous in-the-moment interactions between strangers that might be of value in some way (i.e., meditate serendipitous chance encounters). Therefore, examining matchmaking algorithms in technical detail is beyond the scope of this work. Instead, we will review previous research on the following broad approaches of matchmaking: (1) similarity-based, (2) social-network-based, (3) proximity-based, and (4) preference- / exchange-based.

4.4.1 Profile Similarity

The previously discussed similarity-attraction theory is most commonly used in match computations. Systems typically employ keyword similarity (i.e., shared interests and attributes) as a base assumption to pair users. *Yenta* (Foner, 1997) was one of the first matchmaking agents that aimed to introduce people who share general interests derived from their email and newsgroup messages.

Similar to earlier presented content-based and collaborative recommender methods, the most popular approaches to similarity matchmaking are correlation- and cosine-based similarity calculations (Adomavicius & Tuzhilin, 2005). Correlation-based similarity is based on how much the ratings by common users for a pair of items differ from average ratings for those items, whereas cosine-similarity considers two items and their ratings as vectors, and then mathematically computes the similarity between them as the angle between these vectors. Systems typically use weights to determine importance of information when calculating a match score. Weights represent the strength of a user's interest in a keyword and might be user-defined or system-defined, e.g., using term-frequency inverse user frequency weighting (Chen et al. 2009; Robertson, 2004).

4.4.2 Social Network Data

Several systems have started taking social network data into account when calculating matches between people. This is along the lines of collaborative filtering, i.e., based on the idea that "if many of my friends consider Alice a friend, perhaps Alice could be my friend too". Chen et al. (2009) tested four different algorithms to recommend people on social networking sites: (1) *content-matching* using only profile similarity, (2) *content-plus-Link* adding social network information to the content matching, (3) *friend-of-a-friend* only considering social relationship information, and (4) *SONAR* aggregating social network information from different sources. They found that relationship based algorithms (3 and 4) outperformed content similarity ones (1 and 2). However, they also found that relationship-based algorithms are better at finding known contacts whereas content similarity was stronger at discovering new friends. This is similar to the "People You May Know" feature on Facebook or LinkedIn that suggests new connections based on your existing social network and shared social ties. Furthermore, *Referral Web* (Kautz et al., 1997) combined social network data and collaborative filtering to locate experts in a larger network.

4.4.3 Proximity

Another widely used approach is to incorporate proximity between users into the match computation. As noted earlier, people who are geographically closer to each other tend to be more attracted to each other (Zajonc, 1968). Furthermore, proximity enables matched users to meet face-to-face right away or in the near future. A patent issued in 1979 already proposed the idea of an “on the spot” introduction system, where two people in same immediate area have portable transceivers allowing them to exchange a very limited number of characteristics (Dickson, 1979).

Numerous researchers have proposed mobile prototypes that aim to support proximity-based interaction. In the late nineties, the concept of an *Inter-Personal-Awareness Device* (IPAD) was introduced to support collaboration between people who are in the physical vicinity of each other (Holmquist et al., 1999). Based on this concept, *Hummingbird* was a wearable research prototype that supported communication in co-located groups of people by giving users a continuous awareness of the physical presence (or absence) of others.

Similarly, *GroupWear systems* have been researched to support people in the formative stages of cooperative work. Wearable interactive nametags (called "thinking tags") supported initial interactions between conference attendees by informing them how much they have in common with each other, and allow users to then exchange memes, short ideas or opinions, with each other (Borovoy et al., 1998). Community Mirrors - large, public video displays – were used to reflect real-time visualizations of the unfolding community dynamics back to the users.

The concept of *social devices* was proposed to increase and improve interactions between people and their mobile devices by pro-actively triggering interaction between co-located users in social situations (Mäkitalo et al., 2012; Palviainen et al., 2013; Väänänen-Vainio-Mattila et al., 2012).

Kortuem et al. (1999) investigated how user profiles can be used to support cooperation during physical encounters of individuals and introduced the idea of a wearable system for profile-based cooperation that supports informal communication between individuals who have never met before and who do not know each other. They outline a system called *Proem* that could employ certain user-defined *rules of encounter* between individuals, e.g., “Alert me when I meet a friend of mine”, “Alert me when I meet someone who sells an IBM PC110", "Alert me when I meet someone who went to my junior high school", or "Save a record of everyone I meet who is interested in wearable computing." As a *matchmaker,* the system could alert users to the presence of some yet unknown person who might be interesting to meet. As an *awareness tool,* it could enable users to know the names and company affiliations of other people in a meeting. As a *reminder,* it could alert users to the presence of people they may want to meet or talk to in person, e.g., "When I meet Howard, remind me that I need to get the key from him." As a *diary,* it could keep a record of all individuals that were met during the course of a day. This could be particularly useful when we meet a lot of potentially interesting people we don't know yet, but might want to contact later on, such as during a conference or trade show, e.g., "Tell me who I met today."

Another research application called *Social Serendipity* used Bluetooth and a database of user profiles to recommend face-to-face interactions between nearby users who share common preferences (Eagle & Pentland, 2005). Similarly, *Nokia Sensor* relied on Bluetooth beacons to discover nearby people and to communicate with them (Persson & Jung, 2005). *E-SmallTalker* aimed at supporting the effectiveness of small talk between people in physical proximity by automatically discovering and suggesting topics such as common interests for more significant conversations (Yang et al., 2010). *WhozThat?* shared social networking IDs locally to help facilitate a greater chance of finding others with common interests and to make initial interactions easier (Beach et al., 2008). *PalmGuide* aimed at facilitating knowledge sharing between people with shared interests and experiences, e.g., in museums or conferences, by providing real and/or virtual places for their meetings (Sumi & Mase, 2002). Aldunate et al. (2002) designed an agent-based middleware to support spontaneous collaboration among people in different situations by considering not only the user's knowledge and skills but also physical distance and psycho-social characteristics. Another research prototype called Pro-active Mobile Collaboration Tool (*ProMoCoTo*) aimed at promoting spontaneous collaboration when co-workers met by chance, engaging them in informal interaction and information exchange (Wang et al., 2005).

Commercial mobile social matching systems, so-called *social discovery* apps, using profile similarity and proximity to help users connect to people nearby were said to be 'the next big thing' (Segall, 2012). However, initial excitement ebbed as systems failed to provide value to their users (Hamburger, 2012). For example, *Sonar*[13], a mobile startup that combined publicly available profile information from Foursquare, Twitter, and Facebook with location information, promised to help users discover business contacts and friends around them, but shut down in 2013 after raising nearly $2,000,000 from prominent angels and VCs. *Highlight*[14] is a similar mobile application (still in business as of Jan. 2016) that sends users a push notification when they are near another Highlight user. The general problem is that most social discovery apps either require users to browse through long lists of profiles (i.e., *Sonar*) or the apps send numerous irrelevant notifications based on over-simplified matching algorithms (i.e., *Highlight*). Mobile matchmaking mechanisms are often shallow ("You both like Starbucks"), overwhelming ("36 people nearby want to meet you") and/or are not context-aware ("You both are from New York" while in New York).

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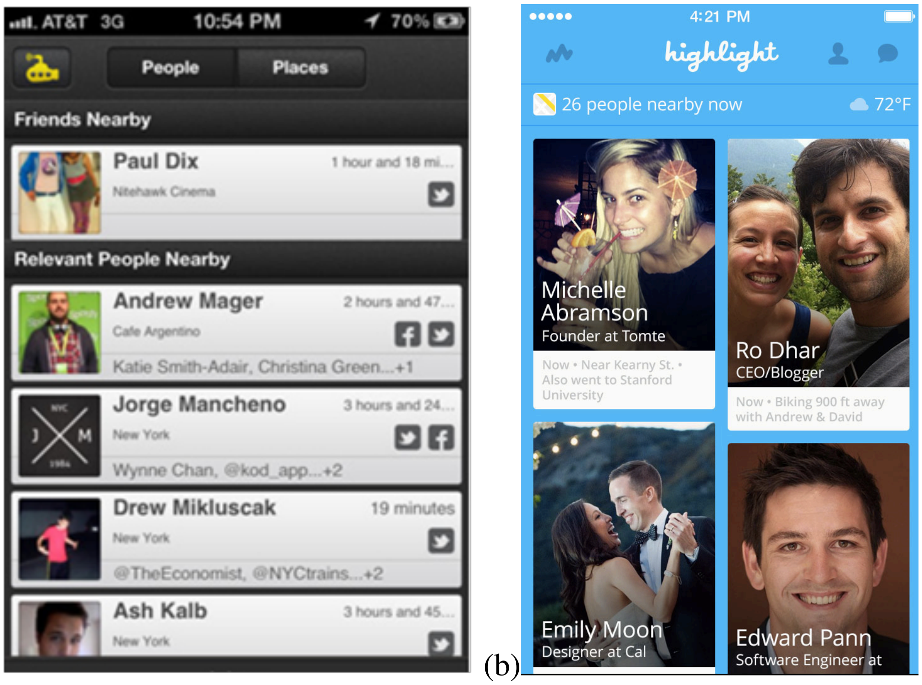
[13] https://www.crunchbase.com/organization/sonar-me (accessed Jan. 2016)
[14] http://www.highlig.ht (accessed Jan. 2016)



(a) (b)

Figure 4.3 Lists of friends / people nearby on *Sonar* (a) and *Highlight* (b).

Source: Sonar [https://www.crunchbase.com/organization/sonar-me, accessed Jan. 2016], Highlight [http://www.highlig.ht, accessed Jan. 2016]

4.4.4 Exchanges and Preferences

Another approach to matching is based on the exchange of resources or services, such as offers and needs. For example, the ride sharing apps *Uber*[15] and *Lyft*[16] matches drivers with users needing a ride. Furthermore, expert recommender systems aim at finding experts for certain information needs of users (Reichling & Wulf, 2009; Streeter & Lochbaum, 1988) (*one-sided*). Another simple yet vastly popular preference-based reciprocal approach is used by the commercial mobile dating application *Tinder*[17]. It presents users a series of photos of people who meet certain age, gender, and location criteria. Users can indicate who they like by swiping their image to the right, and who they do not like by swiping left (**Figure 4.4**). Only if both users like each other, they can message each other. This approach has been shown to be very successful, maybe because

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[15] https://www.uber.com (accessed Jan. 2016)
[16] https://www.lyft.com (accessed Jan. 2016)
[17] https://www.gotinder.com (accessed Jan. 2016)

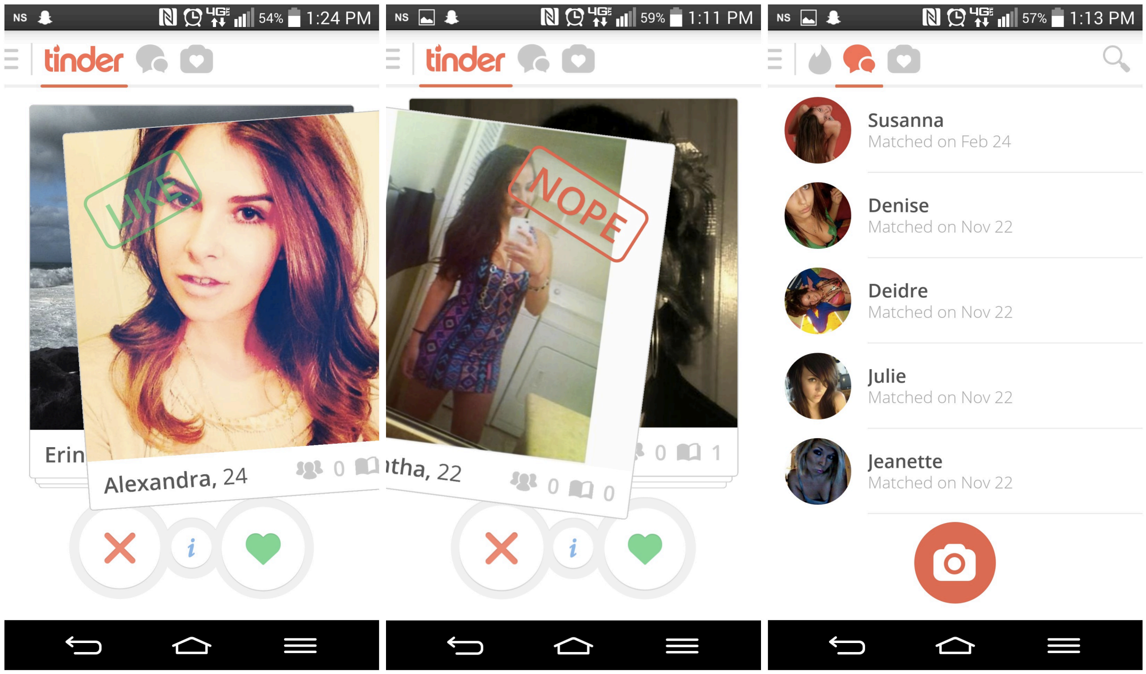

Figure 4.4 Tinder user interface to indicate liking and disliking.
Source: Tinder [http://www.gotinder.com, accessed Jan. 2016]

it is compliant with what people do in the real world: judge people based on appearance.

Taking into account the preference of both parties (*two-sided / reciprocal*), the Gale-Shapley algorithm (Gale & Shapley, 1962) has been widely studied. It deals with the fundamental combinatorial optimization problem of finding a stable matching between two sets of elements given a set of preferences for each element, where every element can only be matched with exactly one other element (e.g., marriage partners, college admission, medical students and hospitals). A matching is stable when there is no alternative pairing in which both individuals would be better off than they are with the party they are currently matched with. To realize this, they developed a mechanism called *deferred acceptance,* which works by having each side of the match state their match preferences (e.g., offers or applications). Those who receive more offers or applications than they can accept then reject their least preferred, but do not immediately accept those they do not reject. They instead hold them without commitment, and acceptances are deferred until the end of the algorithm. In the meantime, those who have been rejected make new offers or applications, which lead to new rejections, until there are no rejected agents who wish to make further proposals. At this point, all proposals that are being held are finally accepted, to produce a stable match market.

Moreover, Expert Recommender Systems (ERS) have been studied in the field of knowledge management to help people find help and locate knowledge and expertise in their social network (Reichling & Wulf, 2009; Vivacqua & Lieberman, 2000). Users can enter a search query for certain knowledgeable users and display an output list of potential experts to find appropriate knowledge carriers (i.e., experts) based on know-how listed in their profile.

4.5 Step 3: Match Notification

The next step in the matching process is informing the user about a social match. Match notifications usually contain information about the other person (e.g., profile picture, name, age, location, other interests) together with some indicator as to why they were matched or the strength of the match (e.g. " You have three things in common" or "82% match"). There are different ways in which users currently are receiving match notifications that can be categorized as pull versus push mechanisms.

Pull mechanisms show a list of recommendations whenever the user logs on to the platform or specifically searches for matches. For example, *CoFoundersLab*[18] is a online platform that offers matchmaking for entrepreneurs and allows users to search for people based on a certain role the person should have, their location and their current status (**Figure 4.5**). *Skout* lets users search for people nearby based on certain criteria, such as search radius (near, city, state, country, world) as well as age, gender and ethnicity preference (**Figure 4.6**).

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[18] http://www.cofounderslab.com (accessed Jan. 2016)

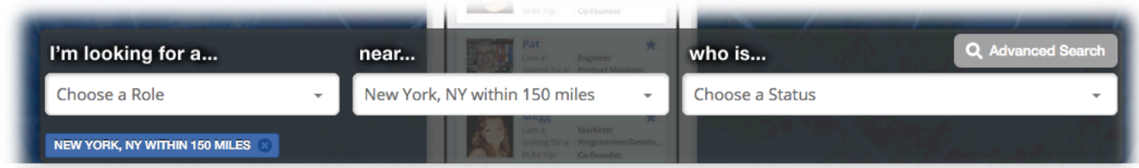


Figure 4.5 User interface for searching for people on the entrepreneur matchmaking platform *CoFoundersLab*.

Source: CoFoundersLab [http://www.cofounderslab.com, accessed Jan. 2016]

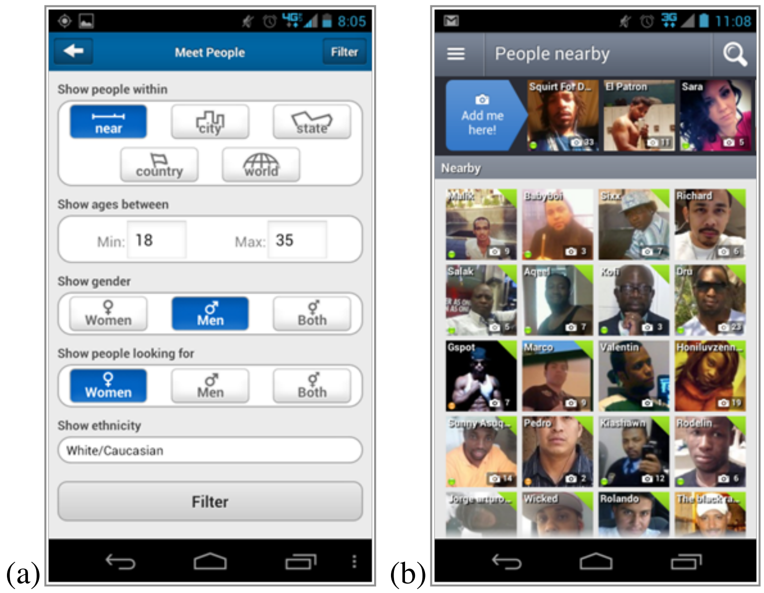


Figure 4.6 People Search on *Skout*: Filter options (a) and list of people nearby (b).

Source: Skout [http://www.skout.com, accessed Jan. 2016]

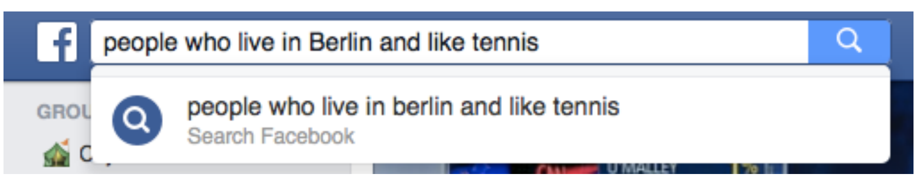


Figure 4.7 Facebook's Graph Search allowing users to search for people.

Source: Facebook [http://www.facebook.com, accessed Jan. 2016]

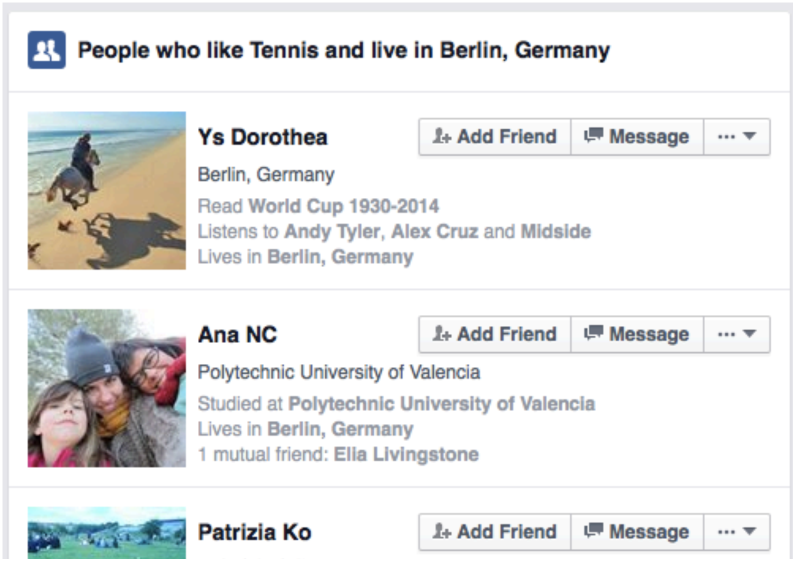


Figure 4.8 Example results of a Facebook Graph Search.
Source: Facebook [http://www.facebook.com, accessed Jan. 2016]

While not a match system per se, Facebook's *Graph Search*[19] allows Facebook users to find interesting people on the platform using natural language queries, such as "People who live in Berlin and like tennis" (**Figure 4.7**). Although some might argue that such people search engines should not be considered social matching systems because their recommendation is solely based on a users search query, they do recommend people to people, even though in a very crude way.

On the other hand, *push* mechanisms send match notifications to users about matches pro-actively, e.g., via email or phone notifications. For example, *OKCupid* sends emails about potential matches (**Figure 4.9**). *Highlight* triggers a phone notification whenever a potential match with a few things in common has been nearby more than once (**Figure 4.10**).

[19] http://search.fb.com/

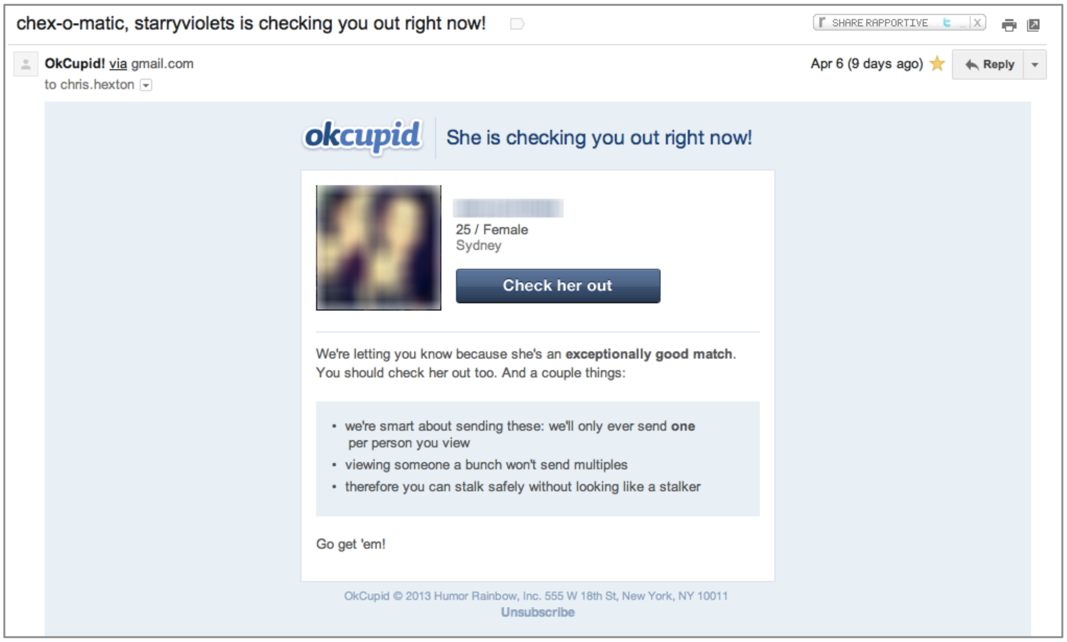


Figure 4.9 Email match notification by *OKCupid*.

Source: OKCupid [http://www.okcupid.com], accessed Jan. 2016]

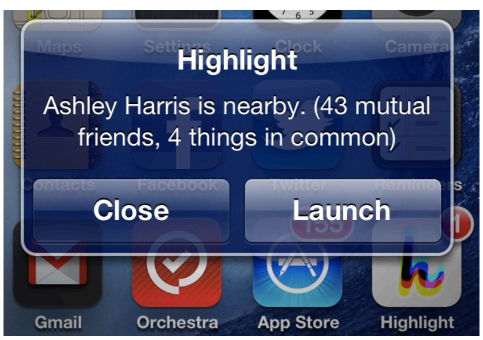


Figure 4.10 Mobile match notification by *Highlight*.

Source: Highlight [http://www.highlig.ht], accessed Jan. 2016]

Most commercial systems use a hybrid of both pull and push mechanisms, allowing users to initiate match request (search and filter) but also sending pro-active match notifications for particularly relevant matches. For mediating chance encounters, we need to explore how push-mechanisms can automatically inform users about encounter opportunities that otherwise might be missed. In a world where users are already being overloaded with spam, alerts and pop-up advertisements, it becomes increasingly important to not overwhelm users with irrelevant match notifications.

4.6 Step 4: Match Introduction

As a last step, social matching systems should support the initial interaction between the matched parties by introducing them. Most matching systems provide simple computer-mediated communication (CMC) tools that enable users to chat and exchange personal information with their matches. A challenge here is to give users control over revelation of their personal information while minimizing privacy concerns and maximizing the chance of a successful introduction. *Progressive identity revelation* is a mechanism that allows strangers to step-by-step reveal certain components (e.g., age, full name, location) of their profile during a synchronous introductory communication (Raban, Ricken, Grandhi, Laws, & Jones, 2009).

Previous research also explored the traditional approach of using common friends to introduce people to each other. *Social Net* (Terry & Mynatt, 2002) uses explicit social network information and RF-based devices to introduce people located in proximity of each other using a common friend. The professional business-networking site "LinkedIn" also uses this approach to ease the introduction between strangers. The platform provides a feature that suggests common friends that could introduce you to a person of interest (**Figure 4.11**).

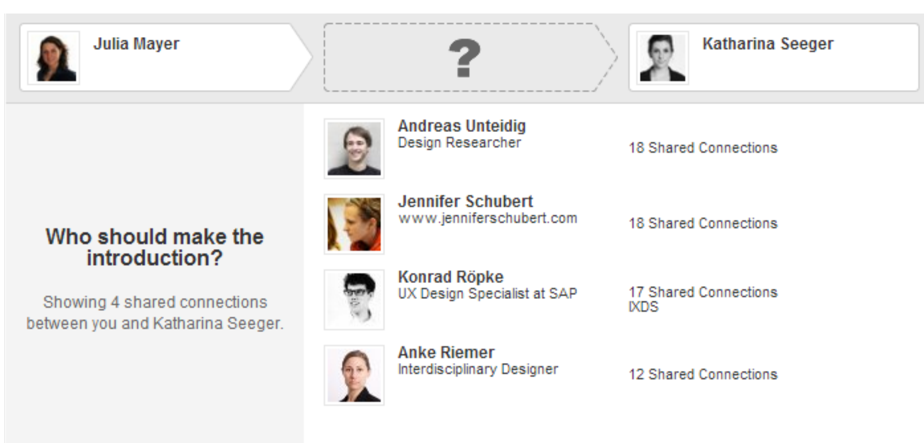


Figure 4.11 Introduction through a common friend on *LinkedIn*.

Source: LinkedIn [http://www.linkedin.com, accessed Jan. 2016]

Prior research has focused on making the introduction between strangers natural and enjoyable through speech and bodily interactions (Mäkitalo et al., 2012; Palviainen et al., 2013; Väänänen-Vainio-Mattila et al., 2012). Researchers proposed body movements and spatial gestures to communicate through the devices with the co-located users. Potential hindrances of acceptance were identified, such as embarrassment about being rejected, having to turn down someone, or disappointment for not finding anyone, among others. Väänänen et al. (2013) point out that in order to overcome these challenges, features that determine when and where users are willing to take part in social interaction as well as contextual and activity awareness are needed in order to make good estimates about when it is appropriate for the system to initiate actions. This aligns with our motivation to support chance encounters by understanding when opportune moments arise and how to identify the right people to introduce to each other in those moments.

4.7 Summary and Open Challenges

In this chapter, we discussed social matching systems, and in particular the different steps of the social matching process, in depth. We gained a deeper understanding about how users could be profiled (step 1) in a dynamic environment using context-awareness and social inference techniques and reviewed different match computation mechanisms (step 2) based on similarity, social network data, proximity and user needs and preferences. Furthermore, we looked at how various commercial systems and research prototypes are currently notifying people about recommended others (step 3) and how they are introducing them to each other (step 4).

Based on this review, several open challenges become apparent. Most research on technology-supported matchmaking focused on building prototypes using profile similarity and proximity, rather than trying to understand users' preferences and the dynamics of chance encounters. However, there is little evidence to suggest that simply adding information about proximity or location histories into interest-based affinity calculations produces particularly relevant matches. With advancement in mobile computing as well as social computing technologies, a primary concern for social matching systems is in providing recommendations in socially intelligent ways based on users' current interests, needs and preferences. Researchers recognize the need for more effective ways to model user context, but to our knowledge, no research has considered more comprehensive contextual data for mobile social matching. Current mobile social matching systems do not have effective mechanisms to introduce interesting people to each other on-the-go and there are considerable theoretical and empirical gaps in our understanding of how to design systems for mediating chance encounter opportunities that otherwise might be missed.

Furthermore, the matching process needs to be made more transparent to users. Current matching systems often inadequately inform the user about the reasons for the match and do not provide adequate control over how matches are computed. This may lead to frustrations and undesired recommendations when users do not agree with or understand the reasons for the system's personalization decisions (e.g., repeatedly being shown the hated ex-girlfriend as a match).

Collectively, system designers and researchers are lacking in-depth understanding of the impact of mobility on chance encounters and their relational, social and personal determinants. In order to mediate chance encounters, we need to understand what constitutes a good opportunity to introduce people to each other. To address the gap in our knowledge about how to use contextual factors to facilitate chance encounters, a more holistic understanding of the relationship between a user's current context and chance encounters is needed. As a first step into this direction, we present prior work that explored contextual factors influencing match opportunities (conducted as part of the author's Master's thesis).

CHAPTER 5

A SURVEY OF CONTEXTUAL RARITY TO IMPROVE MOBILE SOCIAL MATCHING

In Chapters 3 and 4, it was shown that concepts of context-awareness, recommender systems and in particular social matching systems could potentially be used to mediate chance encounters. However, we also learned that there are considerable open challenges still to be addressed. We need to gain deeper understanding of how a user's current context impacts his or her motivation to meet another person. In this chapter, we introduce the concept of *contextual rarity* and how it could be used to improve social matching. Findings are presented from a survey study that was conducted prior to the dissertation research as part of the author's Master's thesis investigating the question of how to leverage contextual data to improve social matching. Results of this prior study are discussed in regards to the implications for this research.

5.1 Contextual Rarity

As noted earlier, previous research and recommendation systems assume that individuals want to be matched with people who are the most like themselves (McPherson et al., 2001). Therefore, current social matching systems apply keyword similarity calculations to predict the desirability of the match. This is problematic because many users can share a large number of similar attributes that do not contribute to the desirability of a match. For example, if the target user demographic is college aged students then many users would share similar attributes related to education level, age, music interests, etc.

Systems can reduce the impact of this by weighting attributes based on a commonness-rarity scale. This is based on the assumption that not only similarity between users but also the rarity of this similarity in the user's current context can be used to calculate relevant matches. The current local context can influence rarity of a shared user attribute. A generally common attribute can become 'contextually rare' in certain contexts. Consider the following possible scenario:

> *Daniel, when on his home university campus in the United States, is surrounded by many other students from his university. In this case being from Daniel's university would not be rare, and so the shared attribute would not result in a match alert. However, when Daniel goes to Italy for an exchange semester, he is excited to be informed about another student from his American university.*

Here, the similarity between Daniel and his match is not strong (the only shared attribute is attending the same university); however it is the rarity of the shared attributes that creates a desired match in the contextual condition. This scenario highlights how a context-aware social matching system, which takes into account an attribute's rarity in the user's local context, can provide contextually relevant social match recommendations.

Moreover, rarity could be used to adjust the search radius for the match. When, for example, there are several people offering tutorials on campus, the search can be constrained to the library but if there only a few tutors around, the search radius can be increased to the entire campus.

This idea is related to earlier discussed concepts that have been applied in data mining and by traditional recommender systems, such as the Term Frequency/Inverse Document Frequency (TF-IDF) measure (Robertson, 2004; Salton & McGill, 1986) and Inverse User Frequency Transformation (Symeonidis et al., 2007) to identify relevant information. Furthermore, sociological research suggests particularly strong forms of solidarity when individuals recognize each other as being from the same minority group (Erving Goffman, 1966; Osbeck et al., 1997). As an example of this, Goffman (1966) states that when fellow nationals meet in exotic lands they may feel obliged or privileged to initiate a conversation.

This seems to be a promising new approach to provide users with more valuable and relevant social matches based on their current context. In particular, the following hypotheses are examined:

> *H1: People's interest in a social match is associated with shared attribute type (e.g., interest, demographics, etc.).*

H2: People's interest in a social match is positively associated with the number of attributes the match is based on (single versus combined attribute matches).

H3: People's interest in a social match is associated with (perceived) rarity of the shared user attribute (relational context).

H4: People's interest in a social match is associated with the participants' match context.

Although the first two hypotheses might seem rather self-evident, they have not been tested for mobile social matching systems. In addition, our goal is to introduce a more comprehensive framework considering mobility of users, by adding H3 and H4, for predicting opportune social matches.

5.2 Method

A personalized self-reported web survey was designed in order to test our hypotheses and learn more about match rarity dynamics. The aim of this study was to investigate the impact of attribute rarity (relational context) and users' current context on interest in a social match. We developed a survey instrument that probed for attribute rarity in four different general contexts (G1-G4) and probed for interest in different hypothetical match contexts (M1-M4) that describe situations in which we think contextual rarity might strongly vary. This way we were able to control for context and focus on the impact of contextual rarity (as part of relational context). We were also able to study the impact of match context at a very general level (i.e., if there is an impact or not, but not specifically how different context types have an impact). This survey did not probe for personal context.

In order to capture *attribute rarity,* we implemented a personalized survey where respondents entered their own user attributes and provided an estimate of the attributes' commonness. For each user attribute provided by participants, we asked "*How common is someone with this attribute in the following context?"* (with a seven-point Likert scale ranging from 'extremely rare' to 'extremely common'). In order to get a broader estimate about rarity, we chose four different general contexts in which respondents had to assess the attributes' commonness: (G1) in your main social circle, (G2) nearby when you go out socially, (G3) at your work/school and (G4) in the area where you currently live (**Figure 5.1**). It is important to note that this question measures the perceived attribute rarity, and does not necessarily reflect actual rarity. However, we believe that people have a good estimate of how rare certain things are about themselves in various situations. Thus, the survey assesses the relationship between people's awareness of how rare an attribute is and their interest in others with this rare attribute. We decided on the wording "common" instead of "rare" to bias participants as little as possible. This measure is referred to as *attribute commonness* below.

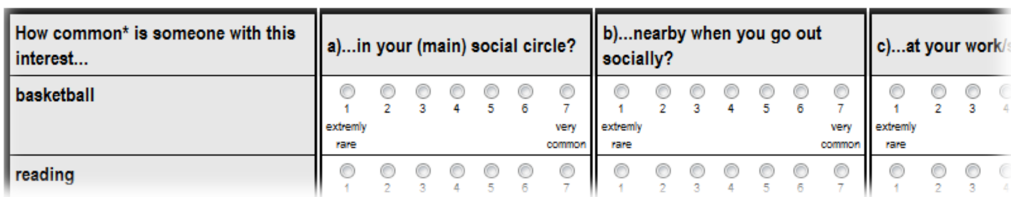


Figure 5.1 Example questions probing for attribute rarity.

Interest was probed by asking participants "Would you be interested in one of the following?" for a variety of matching scenarios providing the following answer options: 'not interested', 'interested in a notification', and 'interested in a notification plus getting introduced' (**Figure 5.2**). To make sure people understood this question, the screenshots shown in **Figure 5.3** together with a short use case scenario were provided to explain to participants what mobile social matching is and how it works. The image on the left shows a match notification that informs a user about somebody of interest nearby and provides a list of shared user attributes. The image on the right illustrates what options a user has after receiving the match notification. A pop-up menu offers to exchange profile information with the match, send a text message or start chatting.

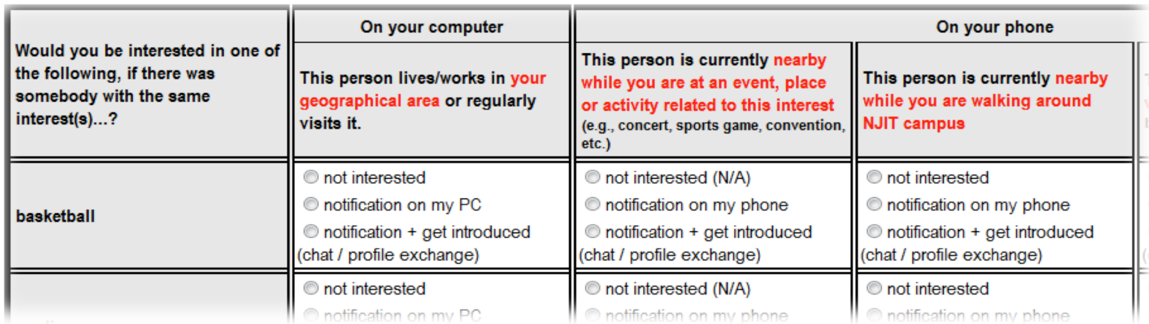


Figure 5.2 Example questions about interest in a social match.

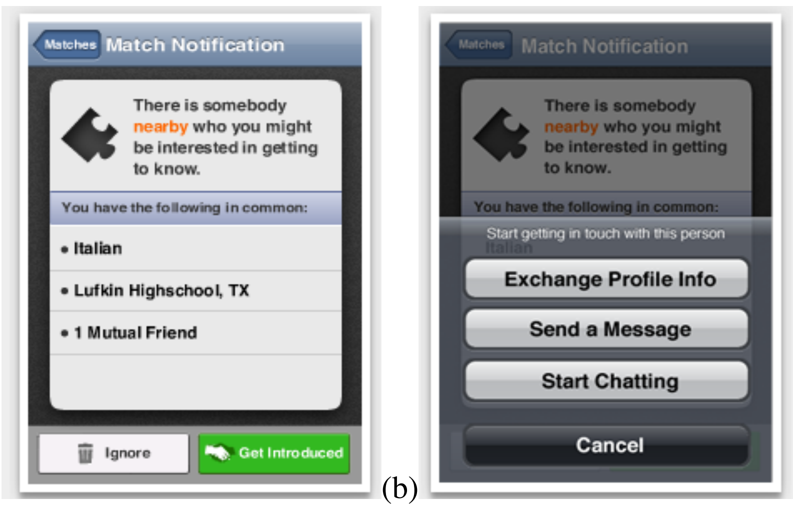
(a) 

Figure 5.3 Mobile social match notification (a) and options to get introduced (b).

To compare interest across different contexts, vignettes that presented respondents with a hypothetical match context were used. Four different match contexts were presented to the respondent. For each match attribute provided by the respondent, the hypothetical match context presented was "*If there was somebody with the same attribute:*

M1 – "On your computer: This person lives/works in your geographical area or regularly visits it."

M2- "On your phone: This person is currently nearby while you are at an event, place or activity related to this attribute."

M3 – "On your phone: This person is currently nearby while you are walking around campus."

M4 – "On your phone: This person is currently nearby while you are in Japan (e.g., for a business trip, exchange semester, etc)."

These contexts were chosen to compare match interest when at home in front of a computer (M1) to when on the go and using a mobile phone (M2-M4). The context M2 assumes that the user attribute is very common because a lot of people with the same attribute can be found at a related event, place, or activity. M3 probes a context that is assumed to be very common for participants (university students, faculty and staff). Being in Japan (M4) is expected to be a relatively uncommon context for students of the U.S. university where the study was conducted and a majority of respondents were assumed not to be from Japan. A note in the survey asked Japanese respondents to assume they are in Italy instead of in Japan. **Table 5.1** provides an overview of survey measures.

Table 5.1 Overview of Survey Measures

COMMONNESS *(1) extremely rare* *…(7) extremely common*	**INTEREST** *(0) Not interested, (1) Interested in notification, (2) Interested in notification & get introduced*
in four different general contexts G1 – In your main social circle G2 – Nearby when you go out socially G3 – At your work/school G4 – In the area you live	in four different **MATCH CONTEXTS**: M1 – On your PC: This person lives/works in your geographical area or regularly visits it. M2 – On your phone: This person is currently nearby while you are at an event, place or activity related to this attribute. M3 – On your phone: This person is currently nearby while you are walking around campus. M4 – On your phone: This person is currently nearby while you are in Japan (e.g. for a business trip, exchange semester).

The following seven attribute types were chosen to compare interest in a social match based on the different types: (A1) Interests, (A2) Needs, (A3) Geographical background, (A4) Educational background, (A5) Distinct characteristics, (A6) Typical Places and (A7) Friends. Accordingly, the survey was split into seven sections, one for each attribute type. In each section, respondents were instructed to enter three of their own user attributes of this type. Attributes entered by respondents automatically appeared in the questions asking about commonness of this attribute and interest in a match based on this attribute (**Figure 4.1**). For each attribute, as well as for the combination of all three in the respective section ("Would you be interested in somebody with the same interests: basketball + hockey + art?"), respondents were asked the same two sets of questions, first rating the commonness and then their interest in different matches. Only for needs, a slightly different approach was used. In this section, respondents were asked to enter 1) something they need a partner for, 2) something they need help for, and 3) something they could offer to others.

At the end of the survey, we also asked respondents to rate their overall interest for each attribute type in terms of getting matched based on attributes from this type. For the complete survey design please see Appendix B.

5.3 Participants, Data Collection and Analysis

Subjects were students, staff and faculty of a medium sized Northeastern United States urban university ranging from 18 to 54 years old. The subjects were invited via email (using university mailing lists and snowball sampling) to take the online survey. The survey took an average of 25 minutes to complete. A total of 117 individuals began the survey. Of these, 89 were complete and used in the results presented here.

Every respondent had to enter 21 attributes (three per attribute type A1-A7). Then for each attribute as well as the three combined attributes per type (except for A2-Needs), *commonness of the attribute* and *interest in match* were measured in four different contexts, which led to 108 commonness and interest ratings per respondent (21 single attributes + 6 combined attributes per type * 4 match contexts), and a total of 9612 (108 * 89 respondents) data points for measurements of attribute commonness and match interest.

5.4 Results

In order to investigate *H_1: People's interest in a social match is associated with (shared) attribute type,* we first look at participants' overall rating of interest for each attribute type in terms of getting matched based on attributes from this type. Respondents reported highest interest in social matches based on shared interests (Mean=4.97, N=89, SD=1.77) and least interest in matches based on shared regularly visited places (Mean=3.39, N=89, SD=1.88). A Kruskal-Wallis H test shows that differences are statistically significant, χ^2 (6) = 34.29, $p < 0.001$, with mean rank interest scores listed in **Table 5.2**.

Table 5.2 Overall Mean Interest Score[a] across Attribute Type

Attribute Type	Mean Interest Score	N	Std. Deviation	Kruskal Wallis Mean Rank
Interest	4.97	89	1.768	367.73
Friends	4.63	89	2.247	343.20
Needs	4.39	89	1.68	312.03
Educational background	4.31	89	1.638	302.78
Distinct characteristics	4.11	89	2.104	293.80
Geographical background	4.09	89	1.915	288.31
Places	3.39	89	1.857	227.15
Total	4.27	623	1.943	

[a] Individual items ranged from 1=not interesting at all to 7=extremely interesting, scales constructed by taking means of items.

Then we turn our attention to participants' stated interest in the different social match situations presented to them. Out of 9,612 match situations, 4,685 resulted in the participant not being interested (48.7%), 2,807 interested in a notification (29.2%) and 2,120 interested in a notification plus introduction (22.1%). In **Table 5.3**, an overview of the frequency distributions of respondents' degree of interest in a social match across attribute types is provided. There are some variations in interest across attribute type. The largest proportion of people reporting interest in a notification plus introduction was for matches based on shared friends (31.5%), followed by matches based on needs (26.3%), then educational background (25.6%), geographical background (25.1%) and interests (17.5%). A Pearson Chi-Square shows the relation between interest and attribute type to be significant (χ^2 (12, N=9612) = 415.524, p<0.001), supporting H_1.

Table 5.3 Frequency Distribution of Interest across Attribute Type

	Not interested		Interested in Notification		Interested in Notif. + Intro		TOTAL
	N	%	N	%	N	%	N
Interest	718	50.4	457	32.1	249	17.5	1424
Needs	397	37.2	390	36.5	281	26.3	1068
Geo. Background	712	50.0	355	24.9	357	25.1	1424
Edu. Background	611	42.9	448	31.5	365	25.6	1424
Distinct Charact.	785	55.1	390	27.4	249	17.5	1424
Places	937	65.8	317	22.3	170	11.9	1424
Friends	525	36.9	450	31.6	449	31.5	1424

Table 5.4 Interest Frequency Distributions for Single vs. Combined Matches

	Not interested		Interested in Notification		Interested in Notif.+Intro		TOTAL
	N	%	N	%	N	%	
Single attribute matches	3594	48.1%	2301	30.8%	1581	21.1%	7476
Combined attribute matches	1091	51.1%	506	23.7%	539	25.2%	2136
Total	4685	48.7%	2807	29.2%	2120	22.1%	9612

For H_2: People's interest in a social match is positively associated with the number of attributes the match is based on (single versus combined attribute matches), we look at the frequency distributions of interest and single vs. combined attribute matches (**Table 5.4**). Because of the large sample size, the differences between single and combined attribute matches are statistically significant (Pearson χ^2 (df=2, N=9612) = 44.244, p<0.01), but they are so small as to not be substantively important. Overall, in both cases, there is close to a 50-50 split between those interested and not interested, with the percentage of "not interested" actually higher for combined-attributes matches. The difference in desire for both a notification and an introduction is only about four percentage points (about 25% of those for combined attributes vs. 21% for a single attribute match). Therefore, H_2 is not supported.

In order to test *H_3: People's interest in a social match is associated with (perceived) rarity of the shared user attribute,* we contrast interest in matches based on extremely rare attributes versus extremely common attributes. To do this, we look at a specific subset of our dataset: people's interest in matches based on educational background attributes while at school (M3). This is considered a very common context for respondents. We then count how often respondents were interested in a match based on a very rare attribute at school and versus based on a very common attribute at school. Because of the relatively small N for this and the following analysis, the responses are dichomized into “Not Interested” vs. “Interested”. Summary statistics can be found in **Table 5.5.**

Chi-square test results show that there is a significant difference in interest for rare versus common attributes, Pearson χ^2 (df=1, N=153) =17.381, p<0.001, supporting H_3. Breaking down interest again, we see that it actually is the *interest in a notification plus introduction* that increases for very rare attributes.

Investigating *H_4: People’s interest in a social match is associated with the participants’ match context,* we again look at people's interest in matches while at school (M3), but this time we only consider geographical attributes rated as ‘7 - very common’ at school. We investigate how interest in a match varies between the common context ‘M3: at school’ and the more exotic context ‘M4: in Japan’, which is considered quite unusual for an US college student. Summary statistics can be found in **Table 5.6**. Chi-square test results show that there is a significant difference in interest for rare versus common attributes, Pearson χ^2 (1, N=106) =4.025, p<0.045, supporting H_4. It is interesting to note that the increase of interest seems to be higher for notifications, not necessarily introductions here.

Table 5.5 Commonness Frequency Distributions for Interest at School in Very Common vs. Very Rare Educational Attribute Matches

	Not interested			Interested	TOTAL
	N	%	N	%	N
1 – Extremely Rare	31	32.6	64 (Notif. 24, Notif.+Intro. 40)	67.4	95
7 – Extremely Common	39	67.2	19 (Notif. 11, Notif.+Intro. 8)	32.8	58
Total	70	45.8	83	54.2	153

Table 5.6 Commonness Frequency Distributions for Interest at School in Very Common Geographical Attribute Matches at School versus in Japan

	Not Interested		Interested		TOTAL
	N	%	N	%	
M3: at school	44	83.0	9 (Notif. 4, Notif.+Intro. 5)	17.0	53
M4: in Japan	35	66.0	18 (Notif. 11, Notif.+Intro. 7)	34.0	53
Total	79	83.0	27	17.0	106

5.5 Limitations

The study is limited by the fact that the survey was conducted in a university surrounding. Another limitation is that the survey relies on self-reported data collection. Self-reported data does not completely reflect people's beliefs and actions in real life situations. Misunderstanding of the question can also contribute to inaccuracies in the data. Obviously, surveys have an inherent limitation regarding their ability to measure impacts of different contexts because, as opposed to direct observation, it is hard to deal with 'context' in survey research. A number of these limitations are addressed by the qualitative study presented below.

5.6 Discussion

Our survey data supported H_1*: People's interest in a social match is associated with attribute type*. This means that system designers should understand and differentiate between different types of attributes of a user profile. Not all types of shared attributes lead to interesting social matches. Respondents rated their interest highest for matches based on shared interests, friends, and needs. This is in line with sociological research (Emerson, 1976; McPherson et al., 2001). For interests, geographical and educational background matches, there was a relationship between rarity of the match and interest, which makes these types of attributes more suitable for matching based on *contextual rarity*. However, for needs-based matches, there was no significant relation between interest and commonness. This could be explained by the fact that explicitly stated needs tend to be less context-dependent and dynamic, and more stable across time and context; a conjecture that needs further exploration.

While many commercial mobile social matching systems focus on location data for matching, our results indicate that matches based on shared places are the least interesting to respondents. We want to point out here that the notion of "place" is a complex concept, and as discussed previously not defined only by physical location but also by activities, people and overall character of the place. Respondents often entered place types instead of actual places, which might have led to erroneous results. For example, being matched with somebody who also regularly goes to *a coffee shop* is very different in nature than being matched with somebody who also regularly goes to the *same exact coffee shop*. Future work should further investigate how places, place types and personal relationships to places influence interest in a social match.

Our results do not support H_2: People's interest in a social match is positively associated with the number of attributes the match is based on (single versus combined attribute matches). This comes as a surprise, since current systems are built on the assumption that the more profile items two people have in common, the better the match. However, we found that combining a number of attributes does not increase people's interest in a match.

H_3: People's interest in a social match is associated with (perceived) rarity of the shared user attribute, was also supported by our results. Therefore, we believe that considering the rarity of a shared attribute in social matching is a promising concept to identify interesting and relevant people. Rarity is highly dynamic and varies across contexts. Future research is needed to understand how systems can implement measures of rarity.

Survey data supported *H_4: People's interest in a social match is associated with the participants' match context*. This is an important insight as it underlines our motivation for building context-aware social matching systems. We conclude that geotemporal and contextual data has high potential to compute more desirable social matches. We also want to note that respondents most often chose only a notification, rather than notification plus introduction, when matches are identified. This leads to an assumption that people are often curious and want to know about a social match, but are hesitant to take the next step of getting introduced through a system.

5.7 Summary

This chapter presented a survey study with 89 respondents assessing how context, and in particular contextual rarity, influences social match desirability. The survey study contributed to our understanding of what factors influence people's interest in a social match, namely attribute type, context, and rarity of the shared attribute. However, new challenges were uncovered, such as the understanding of place, the understanding of needs, and on a broader level, the understanding of what type of contextual information is relevant for social matching. Based on these findings combined with our review of prior work in Chapters 2, 3, and 4, we next present a theoretical framework for opportunistic social matching to guide our research.

CHAPTER 6

THEORETICAL FRAMEWORK FOR OPPORTUNISTIC SOCIAL MATCHING TO SUPPORT CHANCE ENCOUNTERS

The previous chapter showed that context-awareness could be beneficial in social matching systems to mediate chance encounters. Yet there exist considerable theoretical and empirical gaps in our understanding of what aspects of context need to be considered when mediating chance encounters. We introduce the concept of *opportunistic social matching* to mediate chance encounters. Further, based on our review of chance encounter dynamics, we propose a theoretical framework of *opportunistic social matching* that considers more comprehensive contextual data to support chance encounters, such as relational, social and personal context.

6.1 Opportunistic Social Matching

The Merriam-Webster dictionary defines *opportunistic* as "taking advantage of opportunities as they arise" and something is *opportune* when "suitable or convenient for a particular occurrence, occurring at an appropriate time". Terveen and McDonald (2005) first introduced the concept of *opportunistic social matching*. They referred to systems that introduce users without a specific request by a user but instead based on inferred interests from current activity or history of past activity. This is a very broad definition encompassing any system that uses push-mechanisms and implicit user data to match people.

In this work, we refine the concept of opportunistic social matching as it relates to our research. We assume that the right combination of relational context between users and social and personal context of users constitute better opportunities to match users. Therefore, we define opportunistic social matching systems as *context-aware systems that are designed to automatically detect chance encounter opportunities based on* *relational, social and personal context and to ensure that matches are prevented when arising at inopportune moments, and are allowed to occur at opportune moments.*

6.2 Related Work

Related to this concept are *opportunistic networks* (Heinemann, 2007) that form mobile ad-hoc networks between mobile devices while users are in close proximity, with the goal of helping users that are a priori unknown to each other become aware of each other and stimulate spontaneous face-to-face conversation. Similarly, agent frameworks have been developed to encourage and support unplanned *opportunistic cooperation* between people. Based on implicit user profiles from documents and the work environment, agents aim to identify opportunities for collaboration that might otherwise go unnoticed (Vivacqua et al., 2003). Furthermore, the concept of s*erendipitous social networks* (Jang et al., 2011) describes the approach of using individuals' contextual information to connect people in shared immediate situations. While the proposed system focuses on exchanging micro blogging posts between people in the same situation, it does not support matchmaking between users nor recommend them to directly interact and meet. The prototype takes into account location and manually selected activity to infer shared situation. It is noted that further research is needed to understand which facets of a user's situation (e.g., place, time of the day, activity, participating social groups) are correlated with motivation for posting.

6.3 Relevant Types of Context for Supporting Chance Encounters

Based on our examination of chance encounter dynamics, we propose the following types of context as potentially relevant when identifying chance encounter opportunities:

1. *Relational Context*, such as the nature of the relationship between people (including historic interaction patterns), interpersonal attraction based on similarity, complementarity, expected rewards/benefits, and social identity, and

the distance between people.

2. *Social Context*, such as the nature of the place, the people present within that place, crowdedness, social norms, synchronous / asynchronous presence or availability based on time.

3. *Personal Context*, such as the user's personality and current state of mind / mood, as well as involvement in an activity / busyness (as well as future plans / intentions).

Figure 6.1 and **Figure 6.2** illustrate that while relational context depends on the relationship between person A and person B, personal context is an individual attribute. Person A and B could be either in the same social context, same place and time (**Figure 6.1**) or they could be in different social contexts, e.g., different places or time (**Figure 6.2**).

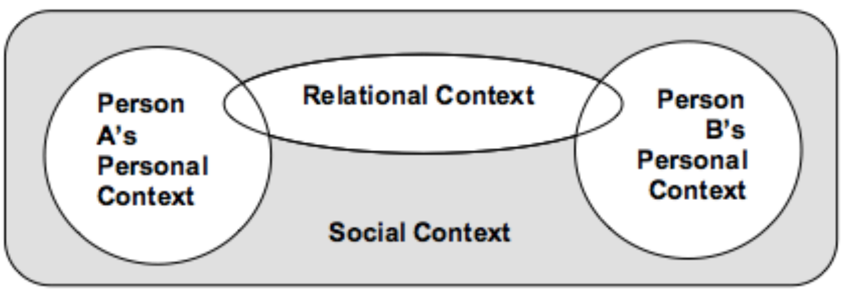


Figure 6.1 Relevant aspects of context of two users in the same social context.

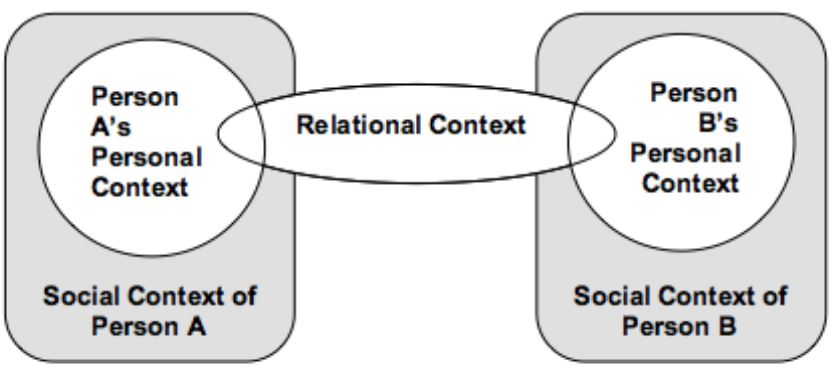


Figure 6.2 Relevant aspects of context of two users in different social contexts.

6.4 Summary

In this chapter, we propose a theoretical framework of social, personal, and relational context as important aspects for identifying such opportunities. This framework systematically orders our knowledge about chance encounter dynamics and provides a lens through which this research will be approached. As a next step, we present our research plan that will allow us to explicate the relationships between different components of the user's context and formalize these relationships.

CHAPTER 7

RESEARCH AGENDA

Building upon previous research (Chapter 2-5) and utilizing our theoretical framework (Chapter 6), we present the research agenda for this work. While our framework proposes relational, social and personal context as predictor of chance encounters, we do not know how these factors interrelate and how they could be inferred and modeled by a mobile system to predict opportunities for chance encounters. We pose overarching research questions that are guiding this work and outline three studies combining qualitative and quantitative methods that will allow us to answer these questions.

7.1 Research Questions

The goal of this work is to map out the design space of opportunistic social matching systems. In order to achieve this, we need to gain a deeper understanding of what constitutes a good matching opportunity, and in particular, how to define, collect and leverage social, relational, and personal context to predict and mediate chance encounters. In particular, the following research questions will be explored:

RQ1: How does current (relational, social, personal) context impact people's motivations to meet new people?

RQ2: How can relational, social, and personal context be operationalized to predict an encounter opportunity?

RQ3: How could mobile systems be designed to utilize contextual information to mediate chance encounters?

7.2 Research Plan

Based on the above research questions, we outline the empirical research plan designed to deliver foundational work in two key research areas: 1) understanding the impact of context on chance encounter opportunities, and 2) system affordances that support chance encounters. These two areas are addressed through three user studies employing qualitative and quantitative methods (**Table 7.1**).

Table 7.1 Research Plan Overview

	Method	Goals
Study 1. **Qualitative Exploration of People's Context-dependent Motivation to Meet Others**	Contextual Interviews	Broad understanding of how current context impacts people's motivations to meet new people
Study 2. **Quantitative Study of the Chance Encounter Opportunity Framework**	ESM study	Operationalize previously found contextual factors and refine framework
Study 3. **Evaluation of the Match Opportunity Framework In-The-Wild**	Field Study	Validate framework and derive system affordances for opportunistic social matching

7.2.1 Study 1

Study 1 is a qualitative exploration of people's context-dependent motivation to meet others. People's actual personal experiences of chance encounters are investigated in regards to relational, social and cognitive determinants of meeting new people in different situations. Since the goal is to probe the mundane details of people's everyday motivations, semi-structured interviews are conducted in different places. Qualitative research is often used to gain a broad sense of phenomena and to form theories than can be used to inform further quantitative investigations. Therefore, this study gives insights regarding the dynamics of chance encounters that provides grounding for the successive quantitative research on relationships and underlying aspects of relational, social and cognitive context.

Extending our theoretical framework, the interview findings are used to further outline how relational, social, and personal context could be used to predict match opportunities and how the different types of context interrelate. Furthermore, we define key constructs and terms, specify classes of variables and general relationships among them, and provide a foundation for the subsequent quantitative study, in the form of variables to measure, issues about which to frame questions, and hypotheses to test.

7.2.2 Study 2

The second study assesses our theoretical framework quantitatively. The goals of this study are to operationalize previously discovered classes of variables and investigate the relationships among them. This is done using an Experience Sampling Method (ESM) (Larson & Csikszentmihalyi, 1983a) tool to collect *in situ* information on a subject's thoughts, feelings or behaviors as they are experienced. Compared to other self-report techniques (e.g., retrospective surveys, interviews), ESM can provide more accurate assessments of everyday behaviors because the data does not suffer from recall bias. Experience sampling has been heavily used for motivation research, health research, as well as in usability research and to evaluate *ubicomp* applications for the past 30 years (Consolvo & Walker, 2003; Froehlich et al., 2007; Hicks et al., 2010; Larson & Csikszentmihalyi, 1983; Schiefele & Csikszentmihalyi, 1995). The core principle of experience sampling is to ask the participants to frequently repeat a very small survey. Typically, such a survey contains a few questions on the research topic and a few questions about the context of the participant. The underlying principle of repeated questioning and contextualizing the answers makes experience sampling highly suitable for research on contextual and mobile computing applications. Expected outcomes include a tested theoretical model with quantified associations between its variables.

7.2.3 Study 3

In a final step, findings from the previous study are used to design a prototypical matching system that is then evaluated through a field study. Following a research-through design approach (Frayling, 1993; Zimmerman, Forlizzi, & Evenson, 2007), we will design an opportunistic social matching system that implements concepts of our theoretical framework. The need for research-through-design follows from the arguments made by Rittel and Weber (1973) that many problems are 'wicked' in that they cannot be accurately modeled or solved through hypothesis testing or engineering approaches. This is because the problem being studied is under-defined, with many possible and contradictory solutions. This provides an opportunity for research-through-design to provide complementary knowledge by proposing ‘better’ as opposed to ‘true’ solutions (scientifically validated) to complex real world problems. The challenges associated with the design and deployment of opportunistic social matching systems are fundamentally under-constrained and therefore an ideal candidate for research through design. As Rittel and Weber (1973) note, wicked problem solutions are ‘one-shot efforts’, which in the interaction design context can be translated as design solutions for a particular time and place, with unique environmental characteristics. We believe that this approach is appropriate for this stage of the research plan as the focus will be on transformative design rather than traditional theory building and testing.

Using scenario-based design methods (Rosson & Carroll, 2003) including personas, storyboarding, wireframing and initial visual design efforts, we create innovative designs for opportunistic social matching. An extended version of the previous ESM study will be used to evaluate the framework as well as the design affordances. The contributions of this study include design artifacts and validated mechanisms utilizing contextual data to introduce interesting and relevant people to each other at opportune moments. Collectively, new innovative system affordances for opportunistic social matching systems will be outcomes of this study.

7.3 Summary

Based on the insights from previous literature, this chapter puts forward a research agenda focused on answering our research questions in regards to how to define, collect and leverage relational, social, and personal context to predict and mediate chance encounters. Three studies combining qualitative, quantitative, and design-research methods are outlined. Collectively, these studies will transform our understanding of chance encounter opportunities, and result in new design affordances for opportunistic social matching. In the following chapter, we present findings from study 1, a qualitative study of people's context-dependent motivations to meet others.

CHAPTER 8

QUALITATIVE EXPLORATION OF PEOPLE'S CONTEXT-DEPENDENT MOTIVATION TO MEET NEW PEOPLE

The previous study gave us a first direction and overview of what influences interest in a mobile social match. It became clear that context plays an important role in mobile encounters. More research is needed to understand the nature of people's context-dependent motivations to meet new people while on the go. There are complex interrelationships, which are not yet fully understood. To address the considerable theoretical and empirical gaps in our understanding, we conducted an interview study to gain a more detailed understanding of how context influences user interest in a social match.

8.1 Research Questions

This study was motivated by the following research questions:

RQ1: What external factors define situations where people are interested in meeting new people? (Opportune social context)

RQ2: What individual factors define situations where people are interested in meeting new people? (Opportune personal context)

RQ3: What relational factors define who people are interested in meeting? (Opportune relational context)

RQ4: How do these factors (social, personal, and relational context) interrelate?

8.2 Method

We chose a qualitative exploratory approach and conducted short semi-structured interviews in various locations to investigate the proposed research questions and to gain a broad understanding of people's perspectives, motivations and attitudes across different contexts. Note that in the use of exploratory interviews, the number of participants is usually small, because the objective is to identify important themes and issues, not to extrapolate statistical findings to a larger population. The research involved several rounds of interviews, data analysis and refinement of our interview guide. The characteristics of the setting / "place" and the activities occurring there were observed and noted before beginning interviews. The initial interviews were conducted with students on an urban university campus with approximately 10,000 students, which was complemented by two rounds of interviews with people in various public places in Manhattan, NYC.

8.2.1 Participants

The focus of the early interviews with students on an urban university campus was to get an initial understanding of the research space, to iterate quickly on findings and refine interview questions. College students are at a point in their lives where they are actively looking to build their social networks and an urban university campus in theory provides an environment that offers numerous opportunities for people to make new connections. Therefore, studying students within this larger urban environment provided a good starting point for learning about people's habits, patterns, and expectations in regards to meeting new people.

Students were randomly approached at different places around campus and asked to participate in a short interview (no incentive offered), similar to market research street intercepts. This approach allowed for the exploration of a variety of locations and quick necessary iterations in our interviews. Interviewers approached a mix of student groups as the study progressed. Most students were willing to be interviewed, with only six out of 52 approached people declining participation in the study, resulting in 46 completed interviews. Interviews ranged from 10-35 minutes, with the average interview lasting for approximately 20 minutes. The average participant age was 21 years old with a range of

18-32. Females made up 28% of participants, consistent with the population of the predominantly male university. Participants had a variety of different majors (business management, biology, mechanical engineering, computer science, digital design, etc.) and about one third of the participants lived on campus while the rest were commuters.

8.2.2 Interviews

Initial interviews on campus were conducted both indoors and outdoors, at locations with defined activities (15 at racquetball courts, soccer field, etc.), social settings (18 at student lounges), and non-social settings (13 at library/academic buildings). The soccer field was described as being used for games of pick-up soccer, but also for cricket, track practice, baseball, etc. Student lounges often provided us with students relaxing with other friends, groups working on assignments, or study sessions. At the library and academic buildings, we interviewed mostly solitary individuals studying or waiting for the next class to start, rather than groups of friends.

After five iterations of interviewing, initial analysis (Hughes, King, Rodden, & Andersen, 1994), and interview guide refining, we conducted in-depth open coding, employing emergent theme analysis of the data collected (Glaser & Strauss, 1967) from our campus based interviews. To reflect on emerged themes and patterns and see if they also held with a more general population and more diverse places, we conducted a second interview study with 12 people in public places around Manhattan, NY, over two days (again, no incentive offered). Here, the average participant age was 32.8, ranging from 22-48 with 50% being female. Interviewees had a diverse professional background (e.g., artist, medical doctor, office worker, film producer, software engineer, etc.). People were interviewed in six different public places around Manhattan, NY: Park (3), train station (3), Ground Zero (3), cafe (2), bar (1). All interviewees were alone except one man was with his wife.

Two slightly different sampling strategies were applied on the two days. The first day, the interviewer approached only people that appeared to be available and potentially open to being interviewed based on observed activity, being alone, and not glued to his/her phone. This resulted in all six approached people agreeing to be interviewed. On the second day, the sampling strategy was slightly modified and people were approached at random (i.e., no matter if they looked busy or available) and interrupted to ask if they would be willing to participate in a short interview. This resulted in 9 of 15 approached people declining to be interviewed. Most people who declined were walking somewhere, said they had to be somewhere or said they "didn't feel like it."

Before we started the interviews, we recorded characteristics of the current situation of a potential interviewee from observation (location, place type, crowdedness, typical activity, etc.). After agreeing to be interviewed, we asked participants questions about their specific situation (what they were doing, how often they were there, who they were with, etc.). Then we delved deeper into their current as well as general interest in meeting new people. We encouraged storytelling by asking about specific past experiences of meeting new people at this or other places and specifically probed for situations where they liked/disliked meeting new people, where they found meeting new people particularly hard/easy and where they faced challenges and frustrations with finding interesting new people to talk to. We further asked them to elaborate on their motivations for interacting with new people and questioned them about their thoughts on being introduced to someone nearby by a mobile app. All interviews were recorded, with the permission of the participant, for later transcription and analysis.

8.2.3 Qualitative Data Analysis

We recorded 926 minutes of semi-structured interviews, which we transcribed and analyzed. For analysis, we followed Grounded Theory approach (Glaser & Strauss, 1967). We combed through the raw data to determine what is significant and transformed the data into a simplified format that can be understood in the context of the research questions (Krathwohl, 1998; Miles & Huberman, 1994). When trying to discern what is meaningful data, we continuously referred back to our research questions and used them as our framework. Then we grouped the data into the meaningful patterns and/or themes using thematic analysis. We used open coding to identify, name, categorize and describe each phenomena found in the data. After that, we continued with axial coding relating codes to each other via a combination of inductive and deductive thinking. Finally, we started drawing conclusions and verified our findings by stepping back and interpreting what our findings mean, determining how they help answer our research question(s), and drawing implications from our findings. To verify our conclusions, we revisited the data multiple times to confirm the conclusions that we have drawn.

8.3 Findings

We discuss our findings below, which are illustrated through representative quotes with names changed to preserve participants' anonymity. The place of the interview is added to the quote when relevant.

8.3.1 Opportune Social Context

Participants generally identified places or situations where they felt it was "okay" to socialize, such as: bars, parties, conferences, organized trips, fraternities, and student clubs. While it may seem obvious to us that a bar is *more social* than a library, it is still difficult for systems to understand and identify opportune social contexts. From interviews, we identified *sociability of people nearby, the familiarity with place and people, perceived safety,* and *jointly attended events/activities* as factors that influence to what extent the current social context for a mobile encounter is perceived as opportune.

A theme that emerged as important when meeting new people was a sense of other people's openness for socializing in the current context. Participants told us that knowing if other people around them were open to meet new people influenced their openness, too. As Jenny put it, *"It's easy to strike up a conversation with someone when the other person seems open."* Fear of rejection might be one reason for that. Several participants told us that they worried if other people were open to meeting new people:

"I'm always scared of bothering someone so that's like a reason why I wouldn't talk to someone in the park because people go there to read a book." (Nicole at Union Square Park, NYC) Participants illustrated how they assess not only their own but others' availability when thinking about meeting new people. Mark told us: *"At the beginning of the semester everyone is looking to meet new people with the influx of freshmen…it sort of sets the expectation of meeting new people."* People seem to have a general idea of how open others around them are for socializing (which may not always be true, e.g., *pluralistic ignorance* (Merton, 1968)). Interestingly, openness to socializing seems to be 'contagious'. When people assume that others are not open to socialize then they will not socialize either. When people assume others are open to socialize, they are open, too.

We further found that familiarity with the people nearby as well as with the current place influenced people's interest in meeting others. Arnold told us, *"When my friends and I went snowboarding, I didn't really talk to anyone new because I was with a group of friends."* Participants were more motivated to meet new people when alone instead of with friends. Not only the fact of being alone instead of with friends, but also being in a new unknown place (e.g., while traveling) may influence interest in meeting others. As John told us: *"I was at a bar in Hong Kong. I don't normally go up to others at bars but saw he was watching a soccer match and was traveling alone, so I started a conversation."*

We repeatedly heard that people are less open to meet new people when they feel unsafe in their environment. Here, the affiliation to a certain place (students on their campus in our case, or being a member of a church or gym) influences this feeling of safety towards meeting others. Other factors like time of the day, crime history, crowdedness, and reputation of a place also seemed to influence perception of safety.

Interview findings show how knowing about others who are at a place for the same reason (event or activity) helps people to connect with each other. Mark told us, *"It's easy to make new friends at certain organized hangouts, and things like different* *events*. Shared experiences makes connecting to new people easier, as Norbert told us: "*I once went bungee jumping in Switzerland and met people on the way to do that. [...] We all kinda bonded, I think because in these moments of fear, these extreme situations make you bond.*" This illustrates how opportune social context could be derived from information about organized events or activities, such as conferences, concerts or clubs.

8.3.2 Opportune Personal Context

Exploring individuals' state of mind, their attitude, ability and willingness to engage in a mobile encounter, we found that involvement in an activity is the strongest predictor of how opportune current personal context is. For example, people in a hurry or busy with something else are rarely willing to meet new people. We talked to Angela in a train station and she said: "*I don't think you meet many people here, because everybody is hurrying somewhere, everyone is going somewhere, people don't have time to stop and chat with you.*" During interviews, people repeatedly told us that they would not want to be introduced to new people when they are busy with something else: "*Anytime that I'm really sort of busy and focusing on something I'm not up to meeting someone new. If I'm in studio, working on something and somebody comes in, my desires to keep on working won't allow my concentration to be broken, more so than to meet them, to get to know them.*"(Marcel)

Compared to that, it seems easier to meet new people while waiting somewhere. As Natasha said, "*Meeting people is easier, for example in a waiting room where there isn't so much outside distraction and it's just they waiting for someone, there is someone who has the same intention as you have, wait for something.*"

We derived another strong indicator of people being less open when busy from our experience with finding participants to interview for this study. Students tended to be less likely agree to an interview at times between classes, as most students were focused on getting to their next class. Similarly, the majority of our declined interviews on campus (5 out of 6) occurred soon before the end of the semester with students citing the need to study as a reason for not participating in the interview. In Manhattan, people who declined an interview (9 out of 15) seemed to be in a hurry, or excused themselves with the reason that they had to be somewhere.

8.3.3 Opportune Relational Context

From our interviews, we found that people's reasons and motivations for meeting certain people vary strongly across contexts. In line with the similarity-attraction effect (McPherson et al., 2001; Morry, Kito, & Ortiz, 2011), having something in common with another person was one of the most mentioned reasons for connecting to a person. Delving deeper into what made these people interesting or relevant to participants, we found that contextually rare shared attributes, contextually rare *not shared* attributes, and activity partnering were the most prominent themes emerging around relational context.

Our prior survey study already explored the idea of *contextually rare shared attributes* used for matching. We again repeatedly heard that people typically were interested in others with whom they share something rare in the current context. When delving deeper, we found that contextually rare shared attributes often are nationality, ethnic minority, religion or extraordinary hobbies. For example, Alyssa from Nigeria told us of the importance of meeting other Nigerians while on her current campus in the United States, *"I found out that [this other person] was also Nigerian, so I introduced myself with that […] and made friends with him because of that. I kind of know all the Nigerians on campus. So I was kind of interested that there was another Nigerian that I didn't know."* Because being Nigerian on an American campus was something unusual to Alyssa, she was interested in meeting any other Nigerian in this context.

Similarly, Scott, who is very religious, explained how his interest in meeting others from his religion varies based on where he is and how common his religion is in that place: "*In my town [my religion] is all over. But here [on campus] it's a lot rarer. Most of my friends from that religion go to [other colleges]."* When asked if he would like to meet others from his religion on campus, he said *"Yeah of course, there are* *always surprises around. That would be cool."*

We repeatedly heard from participants that they would be interested in meeting others that have a certain sought-after skill or interest, usually something that none of their current contacts does or have. Jenny, for example, told us: "*I would totally want to meet somebody right now who does 'international education'. I currently don't know anyone who does that, so I would make the time to have a conversation, definitely. It's what I wanna do next, it's a big career move for me."*

We further found that in some situations people are interested in others because they are both in some way different than the rest of the crowd at a place, i.e., have a *contextually rare but not shared attribute*. In other words, rather than being "birds of a feather" they are the "odd ducks". For example, Arnold, who was at a dinner party with his girlfriend where everybody was an artist, told us: "*I felt like an outsider because I was the only one there who wasn't an artist. But then I found this other guy who also wasn't an artist and we immediately bonded."* Similarly, another participant told of a recent internship she had in Wisconsin. She described the formation of a close friendship with the other external student based solely on the fact that neither of them was from Wisconsin. Pam said, "*When we found out we both weren't from Wisconsin, there was something for us to talk about. Eventually we got to know everyone else who was part of the internship but it was much easier for me to connect with [the other person who wasn't from Wisconsin].*" This illustrates that people do not necessarily have to have a specific attribute in common. Instead, an affinity yields from both *not possessing a common attribute that everyone else possesses (*i.e., everyone was an artist except Arnold, everyone else was from Wisconsin except Pam*)*.

Furthermore, we found that people generally were interested in meeting new people with whom to do an activity of interest. Sue, who enjoys dancing salsa, told us: *"I have a friend who comes with me all the time but she's a girl and it doesn't work because you have to have a guy partner for salsa. We go together but we don't dance together. I* *would like to meet others who dance salsa, especially if they do it here [on campus]."* When it comes to being matched with others for activities, it was important to participants to know their partner's skill level as well as attitude towards the activity. Currently, such assessments were attempted through observation of others but could not be completed due to lacking information (resulting in no initiation of introductions). The action of partner seeking often occurred in the moment and at the location where the activity took place (e.g., soccer field). Examples of partner seeking using skill assessment through observation include players observing other players on the field before inviting them to play a game of soccer or watching one match of billiards before selecting players to join a team.

We found that for activities that have an associated skill, having an alike level was more important for advanced participants than it is for beginners. Lisa told us that she regularly plays chess with her husband. *"He plays very good, he's an excellent player. So playing with him is a big challenge. […] I prefer if they play better than me because it would be a challenge to me."* Amateurs tend to be less restrictive in the type of partner they seek, typically partnering with beginners for recreation or more advanced players for learning. Arnold, who introduced himself as an amateur cricket player said, *"If you're having fun, it wouldn't matter how good they are to me."* For those, it was important to know the attitude with which the activity is performed. Mark said about playing cards with others*: "More important than the skill level is their attitude towards it. If they take it entirely too serious it's not gonna be any fun to play with them. Just knowing that they have a relaxed attitude about it, that they're doing it for fun [is important]."* This shows that in many cases the motivation to meet new people stems from the wish to pursue an activity that requires a partner (salsa, chess) or a group of people (cricket, playing cards). Opportunities for such shared activities might be dependent on current place (e.g., soccer field), current activities offered (pick-up soccer), current nearby people's interests (soccer), position (goalie, attacker, defender), attitude (competing vs. recreational), skill level (beginner vs. advanced), etc.

8.3.4 Interdependencies between Social, Personal, and Relational Context

We found that opportune relational context trumps inopportune personal or social context. In some cases, even if people are *very* busy they want to know about specific *very* interesting people nearby. For example, in the rare case of another person from El Salvador nearby, Aaron would always want to be introduced, no matter how busy: *"I wouldn't consider it an interruption; I can choose to continue the introduction. I'd still like to know I had the chance of meeting another person from El Salvador*." This suggests that while opportune relational context provides the basis for a valuable encounter, social and personal context are mediators either improving or impairing the encounter opportunity.

Furthermore, (in-)compatibility between relational and social context influence people's interest in a match. Interviewees told us about situations where if the reason for the match (relational context) and their current situation or activity (social context) were compatible, they would be more open to introductions, even when busy. Initially, Eugene said, *"I [wouldn't want to meet new people at] the library. Because I'm there to study and I'm usually there by myself trying to keep focus and I wouldn't want people, even like my friends, disturbing me."* But later he admitted*, "It all comes down to what I'm doing. If I'm studying for an exam, [I wouldn't want to be interrupted], unless that person wants to study the same thing that I'm studying, then I wouldn't mind and I would take the time to talk to that person."* In a different case, a participant told us he would not want to meet new people when the reason for the match (relational context) was incompatible with the current activity (social context). Scott, who is very religious and generally interested in meeting others from his religion, said *"I mean I don't want to meet people from my religion if I'm at a party, when I'm doing something I'm not supposed to be doing … You know, I mean I'm human. I do stuff. I wouldn't wanna be doing something that I'm not supposed*."

8.4 Discussion

While some of our findings reflect what can be found in sociology, psychology and cognitive science literature, no prior work has explored how context-aware social matching systems could be designed accordingly.

Our findings regarding opportune social context all underline the importance of systems gaining a better understanding of users' match preferences based on factors like *sociability of people nearby, familiarity with place and people, perceived safety,* and *jointly attended events/activities*. Furthermore, our findings highlight that not only external factors, but also internal factors (personal context), like *mood* and *involvement in an activity* (i.e., the level of how busy or idle/waiting somebody is) should be considered by context-aware social matching systems. In addition to the previously studied concept of *shared contextual rarity* as an indicator of opportune relational context, we found that *outsiders bond,* and particularly in homogenous groups, people are interested in meeting others who also 'don't fit in'. This suggests that systems that could identify outsiders in a confined context could produce highly interesting contextually relevant social matches. Finally, *activity partnering* is a promising concept that could be used to identify opportune relational contexts based on needs and preferences for certain activities, as well as associated skill level and seriousness (competitive or just for fun). We also uncovered some interdependencies among social, personal and relational context. For example, when relational context is very opportune, social and personal contexts seem to play a less significant role. However, when the relational context is less opportune, opportune social and personal contexts are prerequisite for a valuable encounter opportunity. Systems also need to identify if relational context is compatible with personal or social context. It is crucial for future research to understand these interdependencies between personal, relational and social context.

8.5 Limitations

Exploratory qualitative research is aimed at developing an initial understanding of a problem. We used this approach to uncover underlying motivations that influence people's interest in meeting new people across different situations. As with the survey described above, the generalizability of a (mostly) on-campus study of university students to other populations is unknown. Our contribution is to the understanding of factors that influence mobile encounter opportunities, which frames the discussion and sets the stage for quantitative research exploring the magnitude of the phenomena. At this stage, we do not present true measures of mobile encounter opportunities or the computational aspects of the proposed concepts but instead aim at theory construction and raise important issues. Only a limited number of subjects were interviewed, in two locations, a college campus in the Northeast USA and in Manhattan public places. Openness to meeting new people may vary in different geographic locales, such as small towns, different regions of the USA, and other countries.

We are aware of a certain self-selection bias since we only talked to people who currently were open to being interviewed. People who were not willing to be interviewed might have very different motivations for meeting new people. However, our findings will hold for a subset of the population that agreed to our interview (around 40% for the Manhattan group and almost 90% for the campus population).

Moreover, social matching systems rely on the fact that users are willing to share personal information with others. The collection of personal and contextual information requires a thorough understanding of users' privacy concerns. While this study did not directly examine privacy concerns, we do recognize that it is an important issue. Privacy safeguards to protect users will be considered as part of future work to extend the findings presented in this paper.

8.6 Design Implications

Systems need to identify encounter opportunities based on opportune social, personal and relational context. In the sections that follow, we discuss what our findings mean for system design. In particular, we outline how opportune social, personal, and relational contexts could be identified based on contextual user information (that currently is or theoretically could be available on mobile devices). **Table 8.1** provides an overview of these different potential indicators of opportune encounter context. Design concepts stem from our interviews while some of the potential indicators were inspired by our literature review. Several open challenges regarding how systems could obtain an understanding of how opportune a user's current context is, are pointed out along the way.

Table 8.1 Overview of Potential Indicators of Opportune Encounter Context

Social Context	**Personal Context**	**Relational Context**
Contextual Sociability • Place type • Crowdedness • Typical activity at place • Time of the day, week, season • No. of people new to the place • No. of new connections made by others *Contextual Familiarity* • No. of friends in close proximity • No. of prior visits to place	*Contextual Engagement* • Current activity involvement • Scheduled upcoming events • Speed of moving • Self-reported busyness • Self reported mood	*Contextual Rarity* *Contextual Oddity* *Contextual Activity Partnering*

8.6.1 Identifying Opportune Social Context

Interview findings show that the social context greatly influences whether people are interested in meeting others. We propose *contextual sociability* as a measure of opportune social context. While we intuitively know that a bar is more social than a library and an abandoned train station in the middle of the night is less social than a busy airport during the day, systems currently have no means to capture sociability level. We propose to use place characteristics, such as social norms, typical activity and place reputation as well as crowdedness and characteristics of people nearby to infer contextual sociability. Moreover, findings suggest that sociability of others nearby influences whether people are interested in meeting others. In some situations, the time (e.g., beginning of the semester) and the amount of people new to a place (e.g., lots of freshmen) can be indicators of how open people generally are. A direct measure of sociability of others could also be collected from users through unobtrusive user interfaces allowing users to input their openness to meeting others in a quick and easy way in various settings. Another more indirect measure of sociability of people at a place may be the number of new connections between people made at a place. This could be computed based on total connections over an extended time period, seasonally adjusted (e.g., start of each fall semester), or relative to a given point in time (e.g., tonight).

Another concept to identify opportune social context is *contextual familiarity*. We found that familiarity with place and people nearby influence how opportune the social context is. This could be inferred by systems based on the number of friends (or otherwise known people) in close proximity, as well as a measure of how often a user has been to a place before, to inform contextual familiarity.

8.6.2 Identifying Opportune Personal Context

We learned from interviews that involvement in an activity defines how opportune an individual's personal context is. We propose *contextual engagement* as a measure informing us about opportune personal context. Contextual cues such as upcoming/ongoing calendar events at a place (e.g., a gym class or a meeting), the speed at which people move (hurrying somewhere), as well as their current place and current activity type (e.g., studying at the library) can provide hints about *contextual engagement*.

8.6.3 Identifying Opportune Relational Context

Affinities between users have traditionally been computed from similarity and proximity, i.e., a user with shared user attributes or interests in the vicinity. Both our survey and our interview findings dictate that oportune relational context should be the basis of any match. We present three concepts that could be used to infer meaningful relational context: *contextual rarity, contextual oddity and contextual activity partnering*.

Both our survey study and the interview findings indicate that the rarity of a user's attribute in the current relational context is a powerful predictor of how opportune the relational context is. Matching systems could implement this idea by weighting importance of attributes based on the probability of finding another person with the same attribute. Systems could calculate this probability P(A) by dividing the number of occurrences of the attribute n_A by the size of the population N: $P(A) = n_A / N$.

Furthermore, rarity of a user attribute and the probability of finding someone with this attribute are dependent on the size of the user population *N* taken into consideration. Of course, in a mobile environment the relevant user population is highly dynamic over time. While rarity could be calculated globally (i.e., system-wide across all users), the measure only becomes really meaningful when calculated *per context* (e.g., being from a US college while in Italy). However, the size of the population to take into account is challenging to define. Our findings highlighted that *places*, not geographical space, is what defines *social context*. The question is when should a system consider contextual information about just the room a user is currently in (cafeteria), or the entire building, or the neighborhood (or campus), or even the whole town or country. Furthermore, the granularity of the user attributes to be considered needs to be further refined. In some cases, it may make sense to consider a person's interest in 'Sports' in general over their interest in 'Basketball,' or vice versa.

We refer to another design concept we are proposing as *contextual oddity*. In the extreme case of contextually rare attributes not being shared with anyone else in the immediate context, we could identify outsiders to match them. Our findings illustrate how people who do not necessarily have anything in common but are different than the general crowd in the current situation tend to bond more easily. Systems could identify such outsiders in situations where a very high proportion of people share a certain attribute (homogenous groups). This approach presents new opportunities to connect people who are not alike, which is valuable for learning from different people, being exposed to different opinions and mindsets (Granovetter, 1973), and building "bridging" social capital (Putnam, 2000). However, to achieve this computationally, further research into the dynamics of outsiders in mostly homogenous groups and how systems can identify them is needed.

Furthermore, the concept *contextual activity partnering* could be used to match people for activities that are relevant, interesting and available to them in the moment or in the near future. Contextual information regarding the typical activity at the current place as well as users' current activity in addition to users' activity interests could be used to identify and match activity partners near a location where the activity is offered. Systems could provide user interfaces where users can easily enter their needs, i.e., activity partners with a certain skill level. People could then be matched in the moment at the location where the activity is offered. A system could consider matching skill on different levels: 1) Match beginners with somebody to teach them, 2) Match advanced people with somebody to challenge them, 3) Match serious people with somebody to compete with, and 4) Match laid-back people with somebody to have fun with. Further research into how to collect and match people based on skill level and attitude in the current context is needed.

8.6.4 Identifying Relationships and Interdependencies

We earlier defined that *encounter opportunities* exist when two people are (1) interesting or relevant to each other in their current situation (*opportune relational context*), and/or (2) are in a situation where they are willing/able to act on the introduction and start interacting (*opportune social context & personal context*. Along these lines, our interviews illustrated how relational context often provides the basis for an encounter opportunity, while social and personal context are mediators either improving or impairing the encounter opportunity. Once we operationalize these concepts, systems could allow highly opportune relational context overrule less opportune social and/or personal context. Similarly, when the relational context is less opportune, systems could still identify an encounter opportunity based on extremely opportune social and personal contexts.

Study findings further suggest that there are interdependencies between social, personal and relational context. We propose that system designers consider *contextual compatibility* to infer encounter opportunities. While a social match might be possible in one situation, it may not be acceptable or appropriate. An incompatibility between relational context (e.g., contextually rare shared attribute) and social / personal context (e.g., current activity) should be considered by the system as a sign to halt introduction of people. Reducing the likelihood of matches on religion in a wild party environment, or romantic introductions in a workplace setting, may seem obvious but is not addressed by existing matching systems. Similarly, if the reason for the match (taking the same class) and the current activity (studying for that class) are compatible, this should be an indicator to the system that the encounter opportunity is potentially highly valuable to users. Future research needs to operationalize these concepts. Additional quantitative research is needed to measure these strengths of effects and to define opportunity thresholds.

8.6.5 Mediating the Introduction Once an Opportunity is Identified

While this paper focuses on identifying opportunities for valuable encounters, we also want to briefly discuss how context-aware social matching systems could mediate an introduction between two people. Once an opportunity is identified as being valuable enough to inform the user about it, an introduction is triggered. The matched parties get informed about the opportunity and get provided with tools to connect with each other (e.g., messaging, profile exchange). The most crucial part of the introduction is the amount and kind of information that comes with the initial match notification. Enough information to make the value of the encounter obvious has to be revealed but at the same time user privacy has to be ensured. This means that the reason for the match (relational context) should ideally be revealed to the parties concerned to help the introduction process. However, careful consideration of the amount and nature of the information revealed is required. While contextual rarity is good indicator for a social match, in practice people may not be willing to expose such information.

Furthermore, specific information about the social and personal context that contributes to the encounter opportunity being valuable should be conveyed. For example, our interview findings showed how important it is for people to know that others, and in particular the matched person, is currently open to meeting new people. We believe that conveying this information through the app can increase successful introductions.

In addition, we understand that computer-mediated mobile encounters will change the nature of the interaction and are not exactly the same as chance encounters between people without a system mediating. Future work testing an instantiation of a mobile social matching application will explore how such a system itself influences people's perception of how valuable encounter opportunities are in varying contexts.

8.7 Summary

This chapter explored the nature of situations in which opportunities exist for valuable mobile encounters. We further defined our theoretical framework of social, personal, and relational context as important aspects for identifying encounter opportunities. Insights gained from an interview study suggest that opportune social context relates to sociability of people nearby, familiarity with place and people, perceived safety of the location and jointly attended events and activities. Moreover, opportune personal context is mostly reliant on people's current activity and how busy they are. Finally and most importantly, opportune relational context can be identified based on contextually rare shared and not shared attributes, as well as activity partnering. From these findings we derive novel design concepts to identify valuable mobile encounter opportunities based on social, personal, and relational context. These are instrumental in the implementation of context-aware social matching applications.

As a next step, we conduct a quantitative Experience Sampling Method (ESM) study with a larger sample of random participants to explore how social, personal and relational context could be operationalized to identify valuable mobile encounter opportunities.

CHAPTER 9

OPERATIONALIZING CONTEXT FOR OPPORTUNISTIC SOCIAL MATCHING: AN EXPERIENCE SAMPLING STUDY

In this chapter, we build upon our framework and explore how to operationalize relational, personal, and social context to predict match interest. Using a combination of Experience Sampling Method (ESM) (Larson & Csikszentmihalyi, 1983b) and semi-structured interviews enables the sampling of momentary experiences in a variety of contexts to understand dynamic match preferences.

We developed two ESM applications (for Android and iOS) and collected in-situ data from 85 students on an U.S. university campus over four days. Insights from the quantitative ESM data together with the qualitative interview findings extend prior knowledge by identifying the strongest contextual predictors of match interest, and further map out the design space of opportunistic social matching systems.

We start by presenting our hypotheses. A description of the research methods is followed by our results and discussion of our findings.

9.1 Hypotheses

Based on our prior work, the goal of this study is to operationalize proposed constructs of *relational, personal, and social context* in order to further map out the design space of opportunistic social matching systems. Therefore, we put forward the following hypotheses to be investigated:

> *H1: People's interest in meeting a recommended person (match interest) is related to relational context (shared attribute type and contextual rarity).*
>
> *H2: Match interest is related to personal context (mood and busyness).*
>
> *H3: Match interest is related to social context (place type, sociability of people and place, number of people with, safety, organized event, public vs. private place).*

H4: Match interest can best be predicted by combining measures of relational, personal, and social context.

Figure 9.1 shows the analysis model, which was used to guide the collection of empirical data to test our hypotheses.

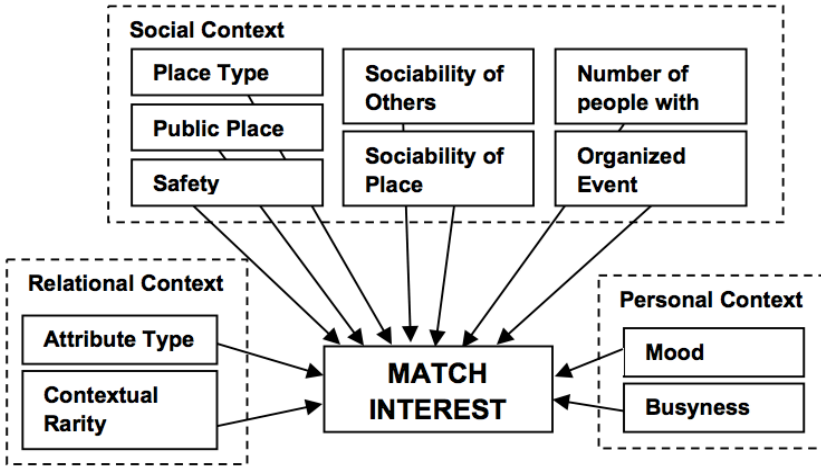


Figure 9.1 Overview of analysis model.

9.2 Method

In this section we introduce the Experience Sampling Method (ESM), present our ESM questionnaire, and describe the post-study participant interviews.

9.2.1 Experience Sampling Method

We chose Experience Sampling (Consolvo & Walker, 2003; Larson & Csikszentmihalyi, 1983b) because it allows the collection of large-scale quantitative data about users' momentary match preferences in a variety of contexts. In an ESM study, participants are signaled (randomly or at set times) several times daily, and at each signal they complete a short survey. Questions elicit information regarding the participants' situation at the moment of the signal, for example their activities, thoughts, mood, etc. This allows for the sampling of momentary experiences in a variety of contexts to understand dynamic match preferences. Furthermore, the advantage of this method is the immediacy of the measurement, as it takes place in individuals' natural environment, which minimizes retrospective biases (Christensen, Barrett, Bliss-Moreau, Lebo, & Kaschub, 2003).

Because ESM samples subjects at random times, it can provide a fairly good overview of major activities that people engage in. At the same time, results from ESM studies tend to miss rarely occurring events and transitions between events. Experience Sampling procedures depend upon the natural incidence of particular events or experiences and do not permit controlled delivery of situational variables (Christensen et al., 2003).

Furthermore, this is a very resource-intensive method because we developed a phone application to be able to trigger notifications at random times and to have personalized surveys and include a user attribute the user can relate to. The development of both an Android and an iPhone ESM application allowed us to recruit a representative sample of university students.

9.2.2 ESM Questionnaire

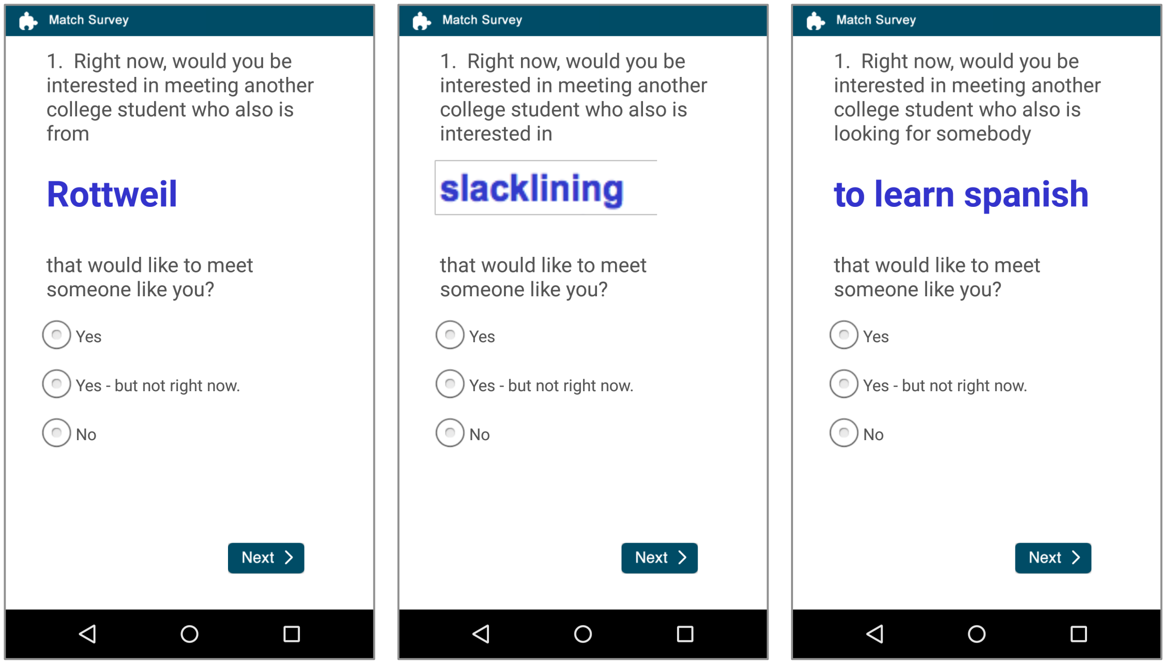
After installing the ESM application on their phone, participants filled out a short profiling survey collecting three demographics (nationality, hometown and current city), five interests, and three needs (e.g., an activity they need a partner for). These attributes were used to operationalize *relational context* in [Q1] and [Q2]. **Table 9.1** shows an overview of all ESM survey construct measures.

Participants received notifications five times per day at random times (between 7am and 10pm). At each notification, participants were first asked if they were interested in meeting another college student (*match interest)* with whom they had something in common (*relational context)* and then how rare the commonality was in the current context (see [Q1] and [Q2] in Table 9.1). The ESM algorithm rotated through previously collected profile attributes and included them in [Q1] and [Q2]. This way, we collected *match interest* for different *attribute types* (demographic, interest, need) and perceived *contextual attribute rarity* [Q2] in each sampled context. Moreover, we asked a series of questions about their current situation (*personal and social context*) (see Table 9.1)

Table 9.1 ESM Survey Construct Measures

RELATIONAL CONTEXT	
[Q1] Attribute Type & Match Interest	"Right now, would you be interested in meeting another student who you share the following with: <attribute>?" [0-No, 1-Yes, 2-Yes, but not now]
[Q2] Attribute Rarity	"Right now, in a radius of 1 mile how many people out of 10 also share <attribute> with you? (Give us your best guess.)" [Select a number between 0-10])
PERSONAL CONTEXT	
[Q3] Mood	Are you currently in the mood to meet someone? [1 - completely not in the mood… 5 - would love to]
[Q4] Busyness	How busy are you with doing a task/activity right now? [1 - extremely idle/bored … 5 - extremely busy]
SOCIAL CONTEXT	
[Q5] Current Place	Where are you right now? [Select from places entered in pre-survey or <add other>]
[Q6] Others' Sociability	How interested in meeting new people do you think others around you are currently? [0-no one nearby, 1-completely not interested … 5-extremely interested]
[Q7] Place Sociability	How social is this place right now? [1 - extremely unsocial … 5 - extremely social]
[Q8] Public Place	Right now, is this a public place? [1 - Yes, 2 - No, 3 - I don't know]
[Q9] No. of People with	How many people that you know are you currently with? [0 - no one … 5 - 5 or more]
[Q10] Safety	How safe do you feel right now? [1 - very safe … 5- not safe at all]
[Q11] Organized Event	Are you part of an organized event right now? [1 - Yes, 2 - No, 3 - I don't know]

Participants were required to complete all questions, which took them 60-90 seconds, keeping the response burden low and resulting in a reasonable response rate. Android application screenshots of [Q1] can be seen in Figure 9.2.



(a) Demographic Match (hometown) (b) Interest Match (c) Need Match

Figure 9.2 Examples of the contextual match preference question [Q1].

After several pilot rounds, the final ESM data collection was carried out March-June 2015. Participants were recruited from an urban university in the Northeast United States via mailing lists, flyers, and the snowball sampling method. A requirement for participation was to own an Android phone or iPhone with a mobile data plan. Successful participation was compensated with up to $25 based on providing a minimum number of survey responses. We used university students due to their high level of sociability and their particular life stage, making them potentially more open to meeting new people and making friends (something that often happens when entering a new life situation (Feld & Carter, 1998)). In addition, students live particularly nomadic lifestyles (Barkhuus & Dourish, 2004), typically monitor their smartphones constantly, and have set schedules (Nathan, 2006), leading to them being flexible in terms of location but needing to plan social life within their already tight schedule.

9.2.3 Participant Interviews

After an initial analysis of data from the first 50 ESM participants, we invited successful ESM participants from subsequent data collection for an optional post-study interview if they had completed surveys at least at three different places, and were available within three days after completing the ESM study (for better recall).

For each interview participant, we printed out all ESM survey responses to be used as a memory aid for discussing specific experiences. Using ESM entries as a memory aid enabled us to collect in-depth insights into real situations and experiences that would have been hard to gather otherwise. We delved deeper into how the different shared attributes included in [Q1] (*relational context)* influenced participants' *match interest* responses. Furthermore, we discussed how *match interest* varied in the different situations captured by the ESM (*personal and social context*). We did this by going over each of the ESM entries with the participant and asked more about the situation they were in when they received (or saw) the notification, and their reasoning behind answering "Yes", "Yes – but not now", or "Later" in those specific situations. Contrasts were drawn by looking at different responses for the same attribute, e.g., "Here you said you were interested in meeting someone who likes *basketball*, but here [different day/time/place], you weren't. Can you tell me more about how these two situations were different?" In addition, the interviews allowed us to assess construct validity of our survey instrument to better understand quantitative results.

Participants were compensated with an additional $15. We voice recorded the interviews with the consent of the participants and transcribed them. For our analysis, we used qualitative content analysis for categorization and constant comparison, looking for themes revolving around our framework of *relational, social* and *personal context* as well as new emerging themes.

9.3 ESM Results

We used SPSS (version 22) to conduct our quantitative data analysis. A total of 163 students signed up for the research study, of which 103 ended up installing the application and filling out the initial user profile survey and a total of 2235 match preference surveys. We cleaned the data and excluded 14 people who filled out less than the minimum required 12 surveys over the course of four days. Furthermore, we removed data from four 'straightliners', participants who consistently responded with "Yes" or "No" to [Q1] (*match interest*). In order to analyze open-ended text entries, such as *profile attributes* and *places*, we combined some entries that had the same meaning (e.g., *USA = America, computer games = video games*) and removed entries that were extremely vague or had no clear meaning. After cleaning the data, we ended up with 557 total profile *attributes* from our 85 participant profiles, 228 of them unique.

Place entries were problematic, since some were extremely broad (*off campus, downtown*) while others were very specific (a certain room in a certain building), or referred to activities (*driving*, *doing laundry*). As discussed earlier, there are several challenges revolving around the *notion of place* in social computing systems (Harrison & Dourish, 1996; Jones et al., 2008; Jones et al., 2004). In order to analyze *place* entries on a high-level, we broke them down into eight categories: *Homes, Educational, Social, In Transit, Business, Work, Sports,* and *Other*.

After cleaning the data, we were left with 1841 survey responses from 85 participants. Of our 85 participants, 58 were male (68.2%), which is consistent with the demographic distribution of the technology-oriented university at which the study was conducted. Participants' ages ranged from 18-38 (mean=22.22, SD=3.89). Most participants were commuters (62.4%) and undergraduate students (82.4%) with a variety of different majors, and from 17 different nationalities (50.6% US American). 55.3% were Android users.

9.3.1 Descriptive Statistics

Overall, participants were interested in meeting the recommended person (i.e., responded 'yes' to [Q1]) in 38.5% of the cases, were interested but not at that moment ('Yes but not now') in 35.9% of the cases, and were not interested ('No') in 25.6% of the cases. This indicates that our participants were generally open to meeting people, saying 'Yes' or 'Yes but not now' roughly 75% of the times.

Table 9.2 Mean Values of Context Variables per Match Interest

	Not Interested (n=471)		Interested but not now (n=661)		Interested (n=709)		TOTAL (n=1841)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Contextual Rarity	3.48	3.55	3.93	3.14	3.90	3.26	3.80	3.30
Mood	1.87	1.05	2.90	1.11	4.02	1.04	3.07	1.36
Busyness	3.53	1.24	3.66	1.11	3.33	1.14	3.50	1.16
Sociability of others	1.95	1.30	2.74	1.23	3.40	1.32	2.79	1.40
Sociability of place	2.69	1.28	3.04	1.19	3.37	1.21	3.08	1.25
No. of people with	1.62	1.73	1.74	1.64	1.82	1.68	1.74	1.68
Safety	1.47	0.79	1.57	0.8	1.44	0.69	1.49	0.76

Table 9.2 compares mean values of the contextual variables for each level of *match interest*. Note that when participants were not interested in the match they rated the shared attribute as rarer (mean=3.48) than when they were interested (mean=3.90). This is contrary to our expectations and prior work (Mayer, Hiltz, & Jones, 2015; Mayer, Jones, & Hiltz, 2015; Mayer, Motahari, Schuler, & Jones, 2010). Our interviews will shed more light on this. Participants' *mood* to meet someone new was much better when they responded that they were interested in the recommended person (mean=4.02) compared to when not interested (mean=1.87). Moreover, participants reported being less *busy* when they were interested in the match (mean=3.33) than when responding with 'yes but not now' (mean=3.66). *Sociability of others* was rated higher when participants were interested now (mean=3.40) or later (mean=2.74), but lower (mean=1.95) when participants were not interested. Along the same lines, *sociability of place* was higher

when interested now (mean=3.37) and later (mean=3.04), but lower when not interested (mean=2.69). On average, participants were with slightly more people (mean=1.82) when they were interested in the match, than when not interested (mean=1.62). Overall, participants rated their current place very safe (mean=1.49). Only minor differences in the average *safety* can be seen across different levels of interest, but when responding with ‘yes but not now’ they rated the place to be the least safe (mean=1.57).

Table 9.3 shows the frequencies of match interest across different place categories, at an organized event and a public versus a private place. When looking at the frequency distribution of interest for each place category, we see that at some places people were more frequently interested (business: 50.0%, social: 44.7%, educational: 42.0%) than at other places. At work people were the least often interested in meeting the recommended person (19.2%%). When participants indicated that they were *at an organized event*, they were interested, but not now the most often (41.5%). Moreover, when participants were in a *public place*, they were interested more frequently (41.2%) than when in a private place.

Table 9.3 Match Interest per Categorical Context Variables

	not interested		interested but not now		Interested		Total	
	n	%	n	%	n	%	n	%
Current Place Category [Q5]								
Homes	242	26.7	319	35.2	344	38.0	905	100.0
Educational	117	21.8	194	36.2	225	42.0	536	100.0
Social	21	24.7	26	30.6	38	44.7	85	100.0
In Transit	24	29.3	27	32.9	31	37.8	82	100.0
Work	28	38.4	31	42.5	14	19.2	73	100.0
Business	5	15.6	11	34.4	16	50.0	32	100.0
Sports	7	25.0	11	39.3	10	35.7	28	100.0
Other	27	27.0	42	42.0	31	31.0	100	100.0
At an Organized Event [Q8]								
Yes	67	24.2	115	41.5	95	34.30	277	100.0
No	401	25.7	545	34.9	614	39.40	1560	100.0
Don't know	3	75.0	1	25.0	0	0.00	4	100.0
In a Public Place [Q11]								
Yes	164	22.9	257	35.9	295	41.20	716	100.0
No	293	27.4	392	36.7	384	35.90	1069	100.0
Don't know	14	25.0	12	21.4	30	53.60	56	100.0
TOTAL	**471**	**25.6**	**661**	**35.90**	**709**	**38.5**	**1841**	**100.0**

9.3.2 Hypotheses Testing

We conducted non-parametric Kruskal Wallis H and Chi-Square tests to test our hypotheses H1-H3. Then we did a correlation and generalized linear mixed model analysis to test H4.

H1: People's interest in meeting a recommended person (match interest) is related to relational context

Looking at *relational context* variables, we found no significant differences in match interest for *attribute type* (Pearson χ^2 (4, n=1841) = 7.454, p=0.114). While differences in mean *attribute rarity* across match interest were significant (Kruskal Wallis H=16.22, df=2, p<0.001), the association seems to be opposite of our expectation and prior work: participants were interested when the attribute was more common.

To better understand this curious finding, we examined content validity of our *contextual rarity* question [Q2]. Participant's stated than on average 3.8 out of 10 people nearby (i.e., 38%) in a radius of a mile shared the attribute included in [Q1] with them. Looking at the different attribute types, we saw that *needs* were rated the most rare, being shared on average with about 33.5% of nearby people in the current context, followed by interests (mean=36.6%), while demographics were rated the most common (mean=44.0%).

However, when we looked at what kind of attributes were rated as extremely rare (max. 10% people have this) we saw *basketball, baseball, music, working out, volleyball, video games, traveling, study, programming, soccer,* and being from the *USA*. This last point highlighted a problem with our data, since more than half of our 85 participants (50.6%) were from the United States, making it the most common nationality. When we computed frequency of attributes across our sample population of 85 participants, we found that the most frequently entered interests were some of the same we earlier found to be rated as extremely rare: *soccer* (found on 42.4% of all profiles), *study* (38.8%), *video games* (31.8%), *football* (25.9%), *basketball* (15.3%) and *music* (15.3%). Hence, participants' ratings contradicted computed rarity across our sample population. Note that since this sample size is rather small, this only provides a rough estimate of what attributes might be more common and which ones are rarer. Nevertheless, we conclude that H_1 cannot be properly tested because of issues with our contextual rarity data. Our ESM profile survey was not collecting really rare user attributes and people were not able to properly estimate *contextual rarity*. We further explored this issue in the interviews.

H_2: Match interest is related to personal context

A Kruskal Wallis H test showed significant differences across match interest at p<0.001 for both *mood*: H(2)=722.34, and *busyness*: H=33.00(2), hence H_2 is supported.

H_3: Match interest is related to social context

Significant differences in match interest were found for being at an *organized event:* Pearson χ^2(4, n=1841)=10.117, p=0.038, and being at a *public vs. private place*: χ^2(4, n=1841)=13.355, p=0.010. Furthermore, we found significant differences in match interest for the different *place types*: χ^2(14, n=1741)=25.171, p=0.033. Kruskal Wallis H tests showed significant differences across match interest at p<0.001 for *sociability of people and place, number of people with,* and *safety*. Therefore, H_3 is supported.

H_4: Match interest can best be predicted by combining measures of relational, personal, and social context

We first investigated correlations between our contextual variables and match interest. While there are several significant correlations (p<0.01) between variables, they are mostly negligible (Pearson correlation r<0.2). However, stronger significant correlations are found between: *mood* and *sociability of others* (r=0.561), *sociability of others* and *sociability of place* (r=0.535), *mood* and *sociability of place* (r=0.362), *sociability of place* and *number of people with* (r=0.287), *match interest* and *mood* (r=0.232). This suggests that mood (*personal context*) is directly associated with *match interest*, while sociability of others and place, and number of people with (*social context*) are associated with each other, and via direct or indirect association to *mood*, also indirectly linked to *match interest*.

We conducted a generalized linear mixed model analysis to predict the relationship between match interest and relational, social and personal context while taking into consideration within-subject correlations as random effect. We ran a generalized linear mixed model with a multinomial distribution and a probit link function using the GENLINMIXED procedure in SPSS. We excluded "I don't know" cases from *at organized event* and *public place*. Therefore, the analysis included a total of 1781 cases. We first entered all our contextual variables into the model and then explored whether any of the non-significant predictors can be removed from the model without having a substantial effect on how well the model fits the observed data. The significance value of each predictor was compared against the Bayesian's Information Criterion (BIC) and was removed if it did not make a statistically significant contribution. Then we re-estimated the model for the remaining predictors. For categorical variables (*at organized event, public place, attribute type, place category*) we used dummy contrasts. Our random effect parameter estimate showed a significant variance of 1.511 (SD=0.328, $p<0.001$) for 'interested' versus 'not interested' and 0.589 (SD=0.157, $p<0.001$) for 'interested but not now' versus 'not interested' as the magnitude of the variability of "personal" coefficients from the mean fixed effects coefficient. Results of the fixed effect coefficients of the terms remaining in the model are summarized in Table 9.4. We see that *busyness, mood,* and *sociability of others* contribute significantly to the full model. The model's BIC is 15805.51 and its overall classification accuracy is 71.1%.

Table 9.4 Fixed Effect Coefficients of the Generalized Linear Mixed Model for Predicting Match Interest

	B	S.E.	t	*p*-value	Exp(B)	95% Confidence Lower	Upper
Interested (now)*							
Mood	1.620	0.0980	16.529	<0.001	5.053	4.170	6.125
Busyness	-0.266	0.0810	-3.286	0.001	0.766	0.654	0.898
Sociability of others	0.363	0.0816	4.446	<0.001	1.438	1.225	1.687
Interested - but not now*							
Mood	0.637	0.0745	8.558	<0.001	1.891	1.634	2.188
Busyness	*0.026*	*0.0633*	*0.412*	*0.68*	*1.026*	*0.907*	*1.162*
Sociability of others	0.165	0.0629	2.625	0.009	1.180	1.043	1.335

*Note that all results should be interpreted in comparison to the reference category "Not Interested".

Our results suggest that a one unit change in *mood* (higher values correspond to better mood to meet people) increases the odds of being interested in a match (relative to 'not interested') more than five times (Exp(B)=5.053). Furthermore, results suggest that participants who were less busy were more interested in a match. For each unit increase in *busyness*, the odds of being interested in the match decrease by 23.4%. Participants, who felt others around them were sociable, were more likely to be interested in a recommended match. For each unit increase in *sociability of others*, the odds of being interested in a match increase by 43.8%.

When we look at how later match interest ('yes but not now') is distinguished from the reference category 'not interested', similar statistically significant positive effects are found for *mood* and *sociability of others*, however *busyness* is not a significant predictor. The value of Exp(B) of *mood* is 1.891, which implies that a unit increase in mood almost doubles the odds that participants are interested in a particular match at a later point in time compared to not being interested at all. The value of Exp(B) for *sociability of others* is 1.180 which implies that one unit increase in *sociability of others* (i.e., others being more sociable) leads to 18% increase in odds of participants being interested in that match not now, but later.

The results, which were tested using a weak measure of relational context (see results for H_1) only partially support our hypothesis H_4*: Match interest can best be predicted by combining measures of relational, personal, and social context*. Only personal and social context seem to play a role in predicting match interest, based on the data analysis.

9.4 Interview Results

We conducted follow-up interviews with 15 participants; 8 female and 7 male students who were 18-24 years old. Interviews lasted on average 34 minutes (range 20-40 minutes) and were all conducted within three days after the participant had finished the ESM study. Names have been changed to preserve anonymity.

We discuss our key findings related to the three topics of *relational context*, *personal* and *social context*. These findings from the interviews provide insights into our ESM study results.

9.4.1 Relational Context

Relational context describes the relationship between people in their current situation, based on the extent and relevance of a shared attribute (e.g. a shared interest, a rare shared profile attribute, a need).

9.4.1.1 Shared Rare Attributes. Supporting previous work (Mayer et al., 2015; Mayer, Jones, et al., 2015; Mayer et al., 2010), participants repeatedly mentioned cases where they were interested in meeting people with whom they share an *attribute* determined to be rare among surrounding people. In particular, they were keen on meeting people they shared rare demographic attributes with, such as nationality and hometown. For example, Nele, a female student from India who grew up in Canada explained during an interview: *"Whenever [current city] came up, I just said "NO" […]. But whenever Canada or India came up, it was far to reach or hard to get, I wanted that."* Kim, even when she was busy, said she was interested in someone who is from Grenada, a little island in the Caribbean where she grew up.

When it came to certain interests, Nicole (from the US) told us, *"I don't meet that many people who like Star Wars, most people think I'm weird for liking it. I think it's a really, really cool series […] and I think people who also like it are cool."* Along the same lines, participants repeatedly mentioned that they do not know a lot of people who like what they like or enjoy doing what they are doing, and therefore definitely would like to meet such people.

Participants seemed to define *rarity* based on how many people they know, hang out with, or know of, who have the attribute in question. A quote from Leon from Brazil, who was in the United States for an exchange semester, illustrates this nicely. Even though Brazilians were determined by Leon to be rare on campus, he did not want to meet more Brazilians, *"because most of the people I hang out here [with] are from Brazil."* On the other hand, Leon would be interested in meeting people who are from the city he currently lives in, which we saw earlier is quite common around campus: *"Yeah, I would be open to people from [current city]."*

A story from Bianca (also Brazilian) provided us an explanation of some of the contradictory ESM results, which showed no relation between perceived rarity of attribute and propensity to want to meet. She explained that she enjoyed painting and did not know anyone in the area who did that; she considered it to be a rare interest (*"Nobody paints, nobody does that! Since I got here I don't know anybody")*, yet she would not want to connect with any others with that interest because it was "her thing" (*"I mean it's just a hobby. […] But this is kind of my thing."*) Some rare attributes were personal interests that participants considered "intimate" and not necessarily something they wanted to share.

9.4.1.2 Meaningfulness and Passion. Another type of *relational context* that we found to influence people's desire to meet up was meaningfulness of, and passion about, an interest or demographic attribute. We found that numerous interests that people listed were not actually that relevant to meeting another person. Raphael (from the US) listed the movie ‘The Avengers’, but clarified in the interview, *“It was just a good movie. It's not something I'd necessarily connect with people over.”* Bianca, however, is a passionate Beatles fan and explains why she would only want to meet others, who are as passionate as her: *“I grew up listening to them because my father loves them. So we have a lot of collections and everything. [...] I don't think I could find people who really like the Beatles. They just say that they do, but I don't think so. [...] If I knew the other person is also very serious about the Beatles, that would change things.”* People’s level of passion can be highly variable for different interests or hobbies, and higher passion seems to positively influence people’s decision to meet a recommended person who shared that attribute with them.

9.4.1.3 Doing an Activity Together: Skill Level and Teaching. Participants also often explained they liked to meet someone for doing an activity together. Raphael told us that it would be nice to meet someone he can bowl with: *“I started bowling during the last semester and I just love it. [...] If I were available I would say ‘Yes’ right away.”*

Skill level was mentioned several times as an important factor when it comes to meeting others for physical or competitive activities. Bianca told us that she used to play volleyball, but was currently not playing anymore because of concerns about matching skill levels with others: *“I know they have a group here but I never joined because I played long time ago and now I don't play that much so I don't want them to think that I really know how to play.”* Another reason people reported being open to meet someone is *willingness to teach*. Mary (from the US) is passionate about Math and mentioned that she would be willing to teach others: “*I tutored here for three years, so [I said ‘yes’ because] I'd be willing to tutor.”*

Overall, the fact that participants were only able to enter interests in general in our ESM profile survey but not their level of passion, rarity in their social circle, or willingness to teach, means that we were not able to predict matching preference in relation to shared interests (*relational context)*. Instead our interviews informed us about how a passionate interest that was not too personal would provide a good foundation for a match, while an interest that was too common or easy to find in others probably would not.

9.4.2 Personal Context

The *personal context* of our participants was their current internal state when they received an ESM probe. We found *mood* and *busyness* to be the strongest predictors of match interest. In the interviews, participants reported that they were interested in meeting a recommended person (i.e., responded with 'Yes') mostly when they were free, bored, or "in the mood" for meeting anyone. Nicole for example, said yes to a match based on her interest in soccer, "*because I didn't have any class in the morning. That would be cool to play soccer with someone in the morning*." Similarly, Mary points out, "*a few times I was like 'Yes', because I was on campus, I was free right now*". Kim explains that she said 'Yes' because: "*I was waiting for my friend in campus center, just on my phone, bored*." And Kim mentioned: "*Sometimes I was just really in the mood, like it would be nice to meet someone new. I just like meeting new people*."

On the other hand, as anticipated, reasons for being interested in meeting someone, but not at that moment (responding with 'Yes but not now') were often related to being busy doing something else: "*I was doing chores*" (Kim); "*I was getting ready for work*" (Lucas); "*I was just getting home, unpacking, having dinner"* (Mary). Relatedly, participants were not interested when they were really busy over an extended period of time: *"I said 'No' because I was in class and I'm not free until 5 pm."* (Mary); *"Thursday morning I was studying for an exam. I was like, NO, I need to focus!"* (Abby) When participants said 'Yes but not now' they often had a better moment for potentially meeting the recommended person in mind already. Mary explained, *"A lot of my answers were 'yes but not now' because I was at work or I was in class. I wanna meet them, but just not at this moment. So if I could meet them in an hour […] I can go."*

These results highlight the more detailed reasons for the ESM finding that *mood* and *busyness* had a great impact on contextual match interest.

9.4.3 Social Context

Social context is the social situation the participants found themselves in at the time of the inquiry. The regression analysis showed only *sociability of others* as a significant predictor of *social context* match interest. Interviews explained why the impact of *number of people with* on match interest was inconclusive. Being at a *place* that implied certain activities (gym, classroom, library) and/or being at an organized event were often mentioned as a reason to postpone the match ('yes but not now'). Moreover, *low sociability of people* nearby and place sometimes made participants want to meet new people. *Safety* of current place was not mentioned as an issue for interview participants at all, which most probably is a result of the study being restricted to only meeting other college students.

9.4.3.1 Number of People Participant Was With. On the one hand, participants mentioned wanting to meet someone when they were alone (similarly to previous work (Mayer, Hiltz, et al., 2015; Mayer, Jones, et al., 2015)): "*I was by myself in a restaurant. It would have been nice to talk to someone who likes [my favorite band].*"(Leon) On the other hand, the *number of people with* increased the match interest in some cases, if adding one more person would not disturb the friendship dynamic. Several participants described wanting to meet someone new because they already were with people: *"Every time I'm with more people, I'm in the mood, I can easily meet more people."* (Bianca) *"There were already so many people so I didn't mind meeting more people."* (Nele)

9.4.3.2 Place Characteristics. We repeatedly heard that people were more open to meeting people when out and about instead of at home: "*I'm more inclined to say 'yes' when I'm out, like at school or at a store. Because when I'm at home I'm more inclined to just stay in bed or talk to my family.*" (Abby) Moreover, we found that certain places that imply being engaged in an activity were often mentioned as reason for responding 'yes but not now': "*When I'm in the library, I usually don't want to socialize or talk with* *somebody*." (Abby)

Furthermore, traveling and being at a new and unfamiliar place, seemed to motivate people to meet others. Leon told us how he was visiting a different city, where he was more interested in meeting someone new: *"When I was in Boston I was more open to meet new people."*

9.4.3.3 Sociability of People and Place. We inferred from the ESM results that the more social the environment is, the more interested people are in meeting someone new. However, similar to the inconclusive results from the *number of people with* presented above, we also heard opposing views on the role *sociability* plays in people's match decision. Abby explained why she said 'yes' to match when she was in an unsocial situation: *"I was in my math class and nobody there speaks to each other. So I was like yeah it would be nice to meet somebody who actually likes to talk."* Here, a low sociability of others nearby and the situation in general triggered her desire to want to meet someone.

These detailed explanations shed more light on the lack of consistent connection between *social context* and willingness to meet someone new.

9.4.4 Compatibility of Relational, Personal and Social Context

It was the "right" combination of the situation and person that lead to most excitement about potentially meeting someone. We received the most enthusiastic feedback from our participants when the shared attribute (*relational context*) matched their current mood or activity (*personal context*) or current place (*social context*). For example, Raphael received a survey notification about meeting someone who also likes his favorite video game, and said 'yes' because: *"I was at friend's house actually playing [this video game]."* John (from the US) experienced a similar situation: *"There was one time where I was studying and 'help me study' came up, so I said ok, yeah."* Relatedly, participants explained that match recommendations were not interesting if the related activity has just ended. Raphael also said ‘Yes but not now’ for a survey on the attribute *working out* with the explanation: “*I just finished working out.*”

Relational context could also be leveraged with places nearby (social context). Leon explains how he envisions meeting someone for a drink near a bar: “*Yeah, I’d be interested in meeting someone who also likes going out for a drink […] especially if we're both near a bar, that would be nice.*”

9.5 Limitations

This study was conducted as exploratory research to understand if/how we could predict match interest. There are several limitations. First, only students served as subjects and the findings might not generalize to other populations. Still, we find that students worked as a very relevant set of people to study because of their highly social nature. Secondly, the demanding nature (participation over several days with surveys required to be filled in daily) could have led to certain types of individuals being over or underrepresented, or to drop out during the study interval. For example, our participants were very interested and open to meet people, saying ‘Yes’ or ‘Yes but not now’ roughly 75% of the time.

Furthermore, it is important to note that Experience Sampling procedures depend upon the natural incidence of particular events or experiences and do not permit controlled delivery of situational variables. Therefore, results from ESM studies might miss rarely occurring events and transitions between events. Also, note that stepwise regression methods have disadvantages. They take important decisions away from the researcher and base them on mathematical criteria rather than sound theoretical logic. However, we based our analysis model on prior work since there were no empirical evidence or sensible theories about which explanatory variables are most important to predict match interest.

9.6 Design Implications

We discuss how *relational, personal,* and *social context* impact match decisions and associated challenges of operationalizing these context types to predict match interest. We then put forward the idea of passive context-awareness for social matching.

9.6.1 Operationalizing Relational, Social, and Personal Context

While prior work repeatedly suggested that *relational context*, and in particular the rarity of the shared attribute, influences the match decision, in our regression analysis neither *contextual rarity* nor *attribute type* were a significant predictor of match interest. However, we found that some of our quantitative data in regards to *relational context* are flawed. We saw that participants' rarity ratings contradicted computed attribute frequencies, and interviews further supported that rarity actually does play an important role in the match decision.

However, interview participants conceptualized *rarity* in a different way than we did in our ESM survey where we had them estimate how many people nearby have a certain attribute. Instead, moving forward, *contextual rarity* should be operationalized based on: (1) *how many friends / others nearby are known to have the shared attribute,* and (2) *how easy to find / discoverable is someone with the shared attribute*. While (1) could be computed based on the rarity of an attribute in the user's social network if the persons nearby are friends in their social network, (2) would require user input.

We further learned that general interests are insufficient to operationalize as *relational context*. Based on the findings, we suggest incorporating users' *level of passion* for interests and activities, as well as *skill level, learning and partnering needs,* as well as *willingness to teach* for activities. Future work is required to test these new ways to operationalize *relational context* to predict match interest.

Both our ESM data analysis and interviews revealed that mood and busyness (*personal context*) are the strongest predictors of contextual match interest. Out of our seven *social context* measures, only *sociability of others* was a significant predictor of match interest in our regression analysis. Unfortunately, there were several discrepancies associated with our other measures. First of all, it was problematic to capture people's understanding of *place* in the survey. Place entries were often too vague or broad to include in our analysis. When looking at interview findings, we saw that participants mentioned a current *place* or *organized event* with an implied activity and resulting *busyness* to explain why they delayed ('yes but not now') or rejected a match. For example, being at the gym usually implies the activity 'working out' and could therefore be interpreted as being busy. Similarly, places like a classroom or the library generally imply being busy studying or attending a lecture. Therefore, we suggest that some place types or characteristics (e.g., typical activity at place) could be used to infer a user's busyness (*personal context*).

Moreover, interview findings in regards to the influence of *number of people with* as well as *place type* on match interest were inconclusive. This seems to be due to a discrepancy between how people currently meet others (reliant on an opportunity) and how they ideally would like to meet people (create their own opportunity). Thus, while it might be *easier* to meet people when the context is sociable (or when already with people), it might be more *desirable* to meet people when the context is not sociable (or one is alone). These discrepancies need further investigation to be fully understood.

Supporting prior work (Mayer, Hiltz, et al., 2015; Mayer, Jones, et al., 2015), we saw again that people were particularly interested in meeting the recommended person when the *relational context* (shared attribute) fits the current *social context* (place or activity). Systems that can reliably detect current activity and current place type could derive encounter opportunities based on compatibility between *relational context* and *social context* (i.e., recommend a gym buddy at the gym).

9.6.2 Towards Passive Context-Awareness in Social Matching

Overall, our study showed how *relational, personal,* and *social context* do not act independently of each other and distinguishing between them is problematic, as the boundaries inevitably merge. Instead of aiming for complete autonomy in predicting opportunities based on sensed information (i.e., *active context-awareness)*, we argue that *passive context-awareness* may be a more user-friendly approach to social matching (Barkhuus & Dey, 2003a; G. Chen & Kotz, 2000). *Passive context-awareness* presents updated context or sensor information to the user but lets the user decide how to change the application behavior, where *active context-awareness* autonomously changes the application behavior according to the sensed information (Barkhuus & Dey, 2003a). Systems could inform users with current nearby encounter opportunities based on *relational context*, but letting the user decide when to act on an opportunity (self-selecting opportune social and *personal context*). From there, users can decide whether the opportunity is interesting enough to act on. Our next study will explore this concept in more depth.

9.7 Summary

This chapter further explored our previously proposed framework of *relational, social* and *personal contex*t as predictors of match opportunities, in order to map out the design space of opportunistic social matching systems. We conducted an ESM study and participant interviews to operationalize *relational, personal* and *social context*. A generalized linear mixed model analysis showed that *personal context* (mood and busyness) together with the sociability of others nearby is the strongest predictors of people's interest in a social match. Interviews further highlighted the role of *relational context* and explained some inconclusive findings. We learned that additional meta-information about user interests are needed to predict matching preference in relation to shared interests (*relational context)*. We propose to incorporate how passionate a user is about an interest (passion level), the attribute's rarity in the user's social circle (social network rarity), or the user's willingness to teach, learn, or try an activity (needs & offers), need to be captured to successfully operationalize *relational context*.

Furthermore, we put forward the novel design concept of *passive context-awareness* for social matching. In summary, this study extends prior research on social matching by providing an empirical foundation for the design of future mobile systems that are more likely to enable opportunistic social matching.

CHAPTER 10

EXPLORING PASSIVE CONTEXT-AWARENESS FOR OPPORTUNISTIC SOCIAL MATCHING: A FIELD STUDY

Our prior work on opportunistic social matching explored people's motivation to meet others nearby with the goal to identify and computer-mediate encounter opportunities. We developed a theoretical framework of relational, social, and personal context to be considered when identifying encounter opportunities (Chapter 6) and investigated and further validated this framework through interviews (Chapter 8) and experience sampling surveys (Chapter 9). The work described in this last study is undertaken as a next logical step in opportunistic social matching systems research. Building upon prior findings, we examine how opportunistic social matching systems could be designed to enable opportunities, instead of just identifying them. As part of this endeavor, we explore how *passive context-awareness* could be used in opportunistic social matching.

This chapter begins with a brief review of the concept of passive context-awareness. We then present our research questions and associated hypotheses. Our methodological approach consists of five components: (1) a profiling survey to operationalize relational context, (2) designing user interfaces of an opportunistic social matching system, (3) the implementation of a mobile application prototype *Encount'r*, (4) a field study evaluating our designs/the prototype, and (5) post-study interviews with field study participants. We present results and findings from each of these steps: (1) we collected 401 user profiles for rarity calculations and relational context operationalizing, (2) we analyzed feedback on more than 3000 encounter opportunities from 25 field study participants (over 5 days), and (3) we discuss qualitative user feedback from 20 post-study interviews. We end the chapter by discussing implications for opportunistic social matching.

10.1 Passive Context-Awareness

We previously introduced the concept of different levels of interactivity of context-awareness in Chapter 3. *Passive context-awareness* presents updated context or sensor information to the user but lets the user decide how to change the application behavior, while *active context-awareness* autonomously changes the application behavior according to the sensed information (Barkhuus & Dey, 2003a; G. Chen & Kotz, 2000).

Opportunistic social matching relies on context information. So far, our efforts were directed towards identifying the perfect opportunity based on relational, personal, and social context. Our previous study showed that the current mood to meet someone and busyness (as part of personal context) as well as sociability of others nearby (as part of social context) were strongest predictors of match interest, while it also uncovered that relational context is crucial and much more complex to model than initially assumed.

Passive context-awareness is a promising approach for opportunistic social matching. Instead of aiming for complete autonomy in predicting opportunities based on sensed information (i.e., *active context-awareness)*, *passive context-awareness* might provide a better user experience for opportunistic social matching. We envision a system that unobtrusively informs users about contextually relevant encounter opportunities nearby, so that users can decide at a glance to act on it or ignore it. In this chapter, we examine how such a system could be designed.

10.2 Research Questions and Hypotheses

In this study, we investigate the following research questions:

RQ1 *Building upon the prior study, how can we <u>operationalize relational context</u> based on attribute rarity, activity skill level, learning/teaching needs and offers to present users relevant encounter opportunities?*

RQ2 *How can we <u>design user interfaces</u> that inform users about relevant encounter opportunities, and allow them to decide when and how to act on them?*

RQ3 *How can we* *derive contextual preferences and rule sets* *based on user behavior, user feedback and response delay/timing?*

Specifically, we test the following hypotheses quantitatively:

H1: *The rarity of shared attribute is positively associated with the acceptance of the encounter opportunity.*

H2: *How passionate a user is about the shared attribute is positively associated with the acceptance of the encounter opportunity.*

H3: *The match type (demographics vs. interest vs. need vs. skills) is associated with the acceptance of the encounter opportunity.*

H4: *The response delay (how fast users act on a match) is associated with the acceptance of the encounter opportunity.*

Collectively, this study contributes both design artifacts and validated mechanisms for opportunistic social matching.

10.3 Method

We followed a research-through-design approach, and designed an IT artifact that we then evaluated in a field study as well as through post-study interviews. The challenge of designing and deploying opportunistic social matching systems is fundamentally under-constrained and therefore an ideal candidate for research-through-design (Frayling, 1993; Rittel & Webber, 1973; Zimmerman et al., 2007). Based on Frayling's (1993) characterizations of design research, *research through design* is different than *research about design* and *research for design*, in that the research contribution is demonstrated by designing and making prototypes. Research-through-design provides an opportunity to create complementary knowledge by proposing 'better' as opposed to 'true' solutions to complex real world problems. In the interaction design context, this means creating design solutions for a particular time and place, with unique environmental characteristics – in our case, university students on a college campus. Research artifacts are different from design practice artifacts in that their focus is to produce knowledge while also demonstrating significant invention, not to make a commercially viable product. In evaluating the performance and effect of the artifact situated in the world, research-through-design helps to discover unanticipated effects and provides a template for bridging the general aspects of the theory to a specific problem space, context of use, and set of target users.

Below we describe the four components of this study in more detail: 1) a user profile survey to enable matching and rarity calculations, 2) the design of an opportunistic social matching application prototype, 3) a field study, and 4) post-study interviews with field study participants to evaluate our matching prototype.

10.3.1 Profiling Survey

For our previous ESM study (Chapter 9), we used a very simplistic approach to operationalize relational context, asking participants to provide any interests and needs as well as their perceived rarity/commonness for each interest. However, we learned that operationalizing relational context requires more detailed user profiles incorporating users' *level of passion* for interests and activities, as well as *skill level, learning and partnering needs,* as well as *willingness to teach* for activities. Moreover, we learned that new approaches to capture attribute rarity needed to be explored. Therefore, we designed a profiling survey that would allow us to collect extensive user profiles including passion levels and skill levels in a quick and easy way from a large amount of participants. This also allowed us to compute baseline attribute rarity scores for a larger user population.

While iteratively designing this survey, we faced two main challenges. On one side, asking open and broad questions, such as "List any interests you have", did not yield very extensive user profiles because people were only able think of a few generic interests, when in fact they had many more interests. Furthermore, this approach did not capture rare and unique user interests and attributes and specific needs. On the other side, we explored asking closed-ended and specific questions for a wide variety of categories, such as music, books, sports, etc. ("What music do you like?" "What books do you like?" "What sports do you like?"). While this yielded much more extensive user profiles, it took participants very long to complete and forced users to go through several categories that were irrelevant to them. In the end, we chose a hybrid of both specific and open-ended questions in the style of "fill-in-the-blank", which pilots showed to be fun and easy for users to complete.

An overview of the profiling data collected in the survey is shown in **Table 10.1**. We collect a variety of user attributes using a total of 26 questions, sectioned into "Demographics", "School & Work", "Hobbies & Interests", "Needs & Offers", and "Skill Levels". While Q1-Q7 as well as question Q9-Q12 were mandatory to be filled, the other questions could be left empty if they did not apply to participants, but users were encouraged to enter as many items as they could think of (as shown in **Figure 10.1**). After collecting all user attributes, participants were asked to rate how passionate they were about each of the interests, activities, and hobbies they entered, using a 5-point Likert scale anchored by "not at all passionate" to "extremely passionate" (see **Figure 10.2**). Moreover, we captured participants' sociability using a 12 question measure from Cheek & Buss (1981), using a 5-point Likert scale anchored by "extremely uncharacteristic" to "extremely characteristic" (**Table 10.2**).

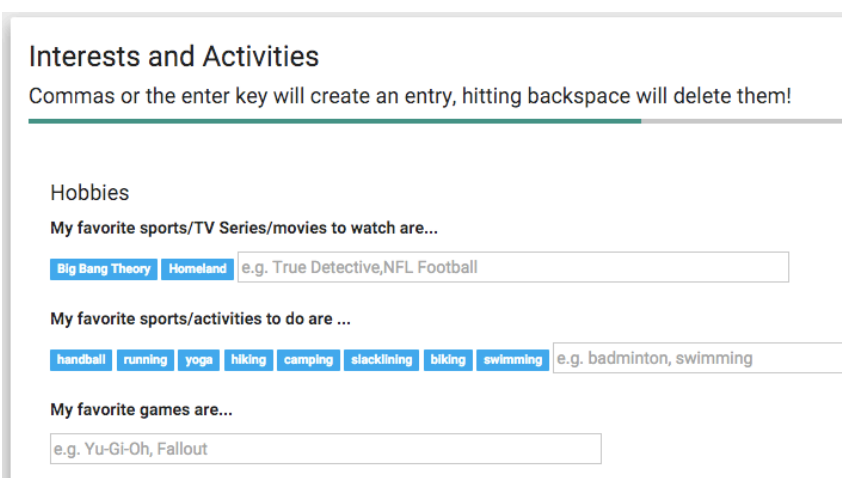


Figure 10.1 Example of "Interests and Activities" section of profiling survey.

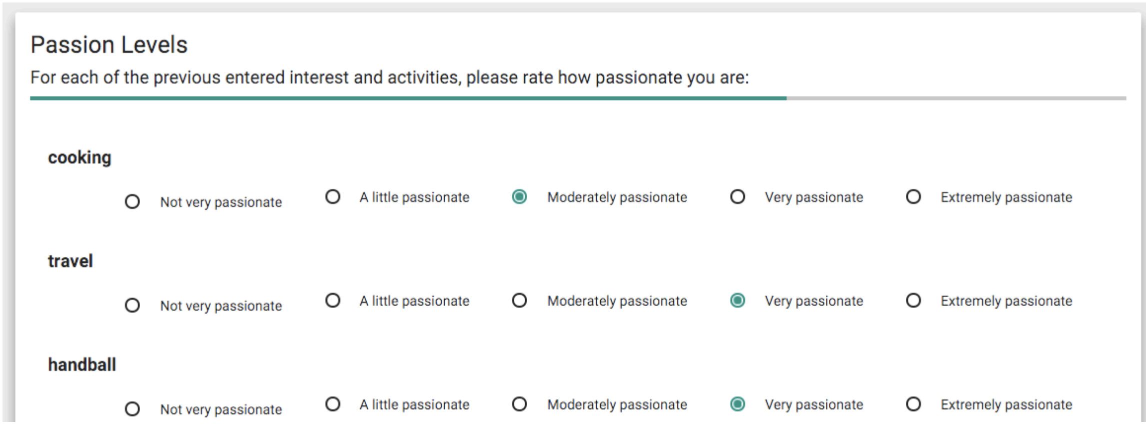


Figure 10.2 Example of passion level questions.

Table 10.1 Overview of User Attributes Collected in the User Profiling Survey

DEMOGRAPHICS			
1. Age	2. Gender	3. Relationship Status	4. Nationality
5. Hometown	6. Current City	7. Native Language	8. Other language(s)
SCHOOL & WORK			
9. Student Type (undergrad / grad)	10. Status (full/part time)	11. Commuter / Live on campus	12. Major
13. Campus Organization	*"I'm involved in the following campus organizations…"*		
14. Work Field	*"I'm currently working in the field of…"*		
INTERESTS & HOBBIES			
15. Watch	*"My favorite sports/TV series/movies to watch are..."*		
16. Activity	*"My favorite sports / activities to do are…"*		
17. Game	*"My favorite games are…"*		
18. Interest	*"Other favorite things I like are…"*		
19. Unique Interest	*"Something I like, but none of my friends like are…"*		
20. Try	*"I always wanted to try …"*		
NEEDS / OFFERS			
21. Looking for	*"I'm looking for people for …"*		
22. Help	*"I need some help with… "*		
26. Willing to teach	*"Things I'm willing to teach / help out others with are…"*		
SKILLS			
23. Learn / improve	*"I would like to learn / get better at..."*		
24. Expert	*"I'm really good at …"*		
25. Beginner	*"I just started learning / doing…"*		

Table 10.2 Sociability Measure from Cheek & Buss (1981)

1. I like to be with people.
2. I welcome the opportunity to mix socially with people.
3. I prefer working with others rather than alone.
4. I find people more stimulating than anything else.
5. I'd be unhappy if I were prevented from making many social contacts.
6. I am socially somewhat awkward.
7. I don't find it hard to talk to strangers.
8. I feel tense when I'm with people I don't know well.
9. When conversing I worry about saying something dumb.
10. I feel nervous when speaking to someone in authority.
11. I am often uncomfortable at parties and other social functions.
12. I am more shy with members of the opposite sex.

The survey was implemented as an online multi-section form with data stored in a PostgreSQL[20] database. The server-side code was written in Scala using the Play[21] framework in an attempt to utilize a framework that would scale effortlessly as our application complexity grew. Users initially logged into the system using Google OAuth via their university webmail address. Then, participants signed an online consent form approved by the university IRB and were informed that the profiling survey is for mobile social matching research and that they might be invited to participate in a field study. They created a 'profile' by answering the survey questions, which were then subsequently stored in the database. The survey took an average of 10-15 minutes to complete. For the full survey see Appendix C.

10.3.2 Mobile Application Design Process

In parallel to the survey design, we also designed an opportunistic social matching application that incorporates all knowledge accumulated over the course of this research. We followed an iterative scenario-based design (Cooper, Reimann, & Cronin, 2007; Rosson & Carroll, 2003) using design tools, such as personas, scenarios, storyboarding,

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[20] http://www.postgresql.org/ (accessed Jan. 2016)
[21] https://www.playframework.com/ (accessed Jan. 2016)

and wireframing, and cycled through an active process of ideating, iterating, and critiquing potential solutions.

We focused on the same target population as in our previous work, university students, since they proved to be highly appropriate and social due to their life stage (Barkhuus & Dourish, 2004; Feld & Carter, 1998). In brainstorm sessions, we collected a variety of possible match scenarios that allowed us to explore a variety of encounter opportunity situations, as well as different actions a user might want to take on an opportunity (Figure 10.3).

Figure 10.3 Brainstorming and card sorting sessions.

Exploring how to design for such scenarios, we identified three main design components of the application to be designed: 1) the *Match Notification*, informing users about relevant nearby encounter opportunities at the *right* time with the *right* amount and type of information about the match, 2) the *Match Screen,* presenting relevant additional details about the matched person, and 3) *Match Feedback Screens,* collecting feedback about matches to derive rule sets and user preferences.

Table 10.3 Example Match Scenarios

Steve is a 21-year-old Sophomore Business major who plays chess. He likes to play with anyone he finds that also enjoys chess, and plays online chess as well…	
…Steve is walking into the lobby of the dorm where he lives, as he receives a notification that Nick is nearby and likes to play chess. Steve has just finished his last class so he is very much ready to play chess and relax with someone after a long day, so he acts on this match.	*…Steve is currently in his night class for Econ201. During the break of this 3-hour class he checks his phone and sees that he has a notification to meet someone to play chess at that time. Since he is still in class, he is unable to accept the opportunity at the moment, but would like to after class, or at a later date.*
✓ Relational [chess] ***✓ Personal [finished with class]*** ***✓ Social [in the lobby of the dorm]***	***✓ Relational [chess]*** ***✓ Personal [on break]*** ***✗ Social [in class]***
Anna is a 20-year-old student from Toronto. She very much enjoys curling, but that is not so popular here in America where she goes to school. Anna currently does not have anyone who she can curl with, but used to curl very often at home…	
…The Spring semester is finally over and Anna is heading back home to Toronto to her old family and friends. She gets a notification that someone is nearby at NJIT who also enjoys curling. She is leaving tomorrow morning, so acting on this now would be unreasonable. However, she would still like to meet this person when she gets back on campus in the Fall Semester.	*…Anna is currently at a Curling game and during a break she gets a notification that someone is nearby who is also interested in Curling. This does not interest her, because she is currently with her team, and nearly everyone watching the match is most certainly interested in curling.*
✓ Relational [curling] ***✗ Personal [leaving home tomorrow]*** ***✓ Social [on campus]***	***✗ Relational [curling currently very common]*** ***✗ Personal [with her team]*** ***✗ Social [at a curling game]***
Caitlyn is an 18-year-old Freshman Computer Science major. She is looking for someone to help her with her classes, as she hasn't experienced anything this difficult yet, and really needs help, especially in Math…	
…Caitlyn is studying for the first Calculus I common, and she receives a notification that someone is nearby that may be able to tutor her in Calculus, so she accepts it.	*…Caitlyn has just finished her first Calculus I common, and she receives a notification that someone may be able to tutor her. She just finished the exam, so now would be too late for this match to be interesting to her.*
✓ Relational [Calculus] ***✓ Personal [studying for Calc]***	***✗ Relational [Calculus exam finished]***

As a next step, we started sketching out scenarios using storyboards and wireframes on white boards (**Figure 10.4**) and later built paper prototypes to design the interaction between the user and the system (**Figure 10.5**), before moving on to *Axure*[22] for low fidelity mockups (**Figure 10.6**). Final high-fidelity designs were later created using *Sketch*[23] and are presented in the next section.

[22] http://www.axure.com (accessed Jan. 2016)
[23] https://www.sketchapp.com/ (accessed Jan. 2016)

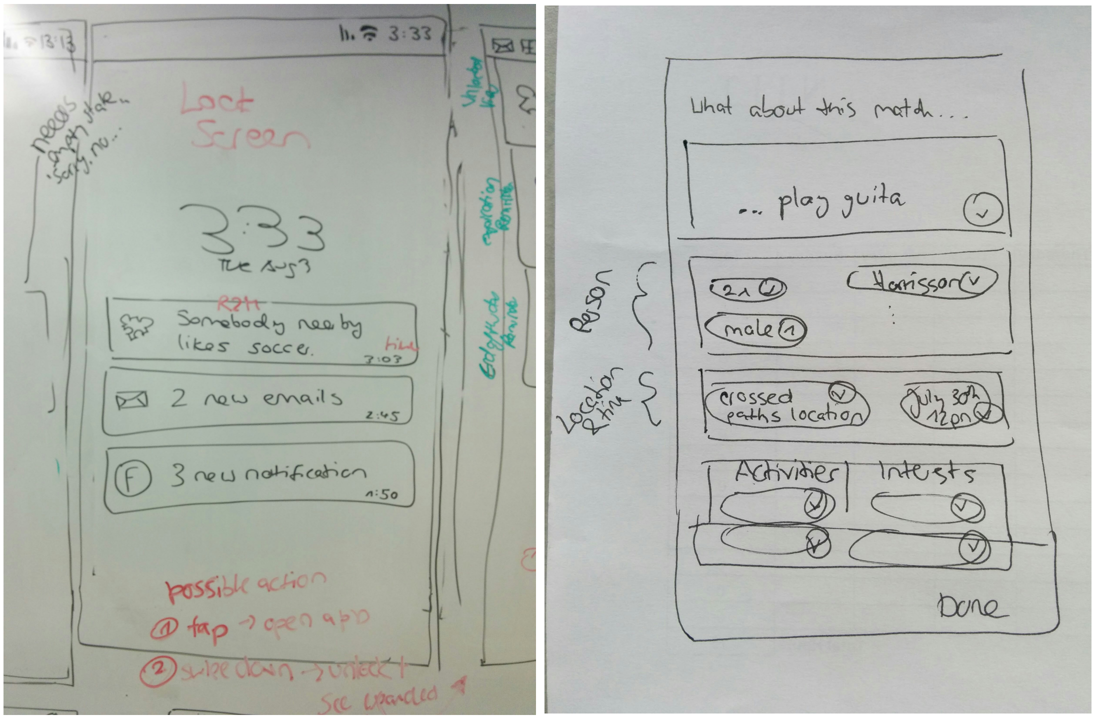


Figure 10.4 Early wireframes of the match notification (left) and match screen (right)

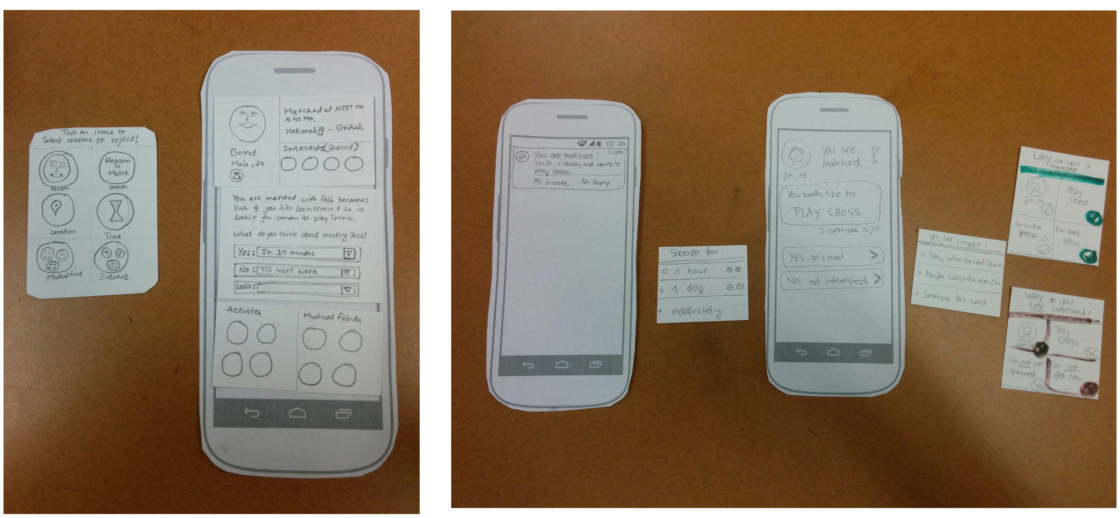


Figure 10.5 Paper prototypes.

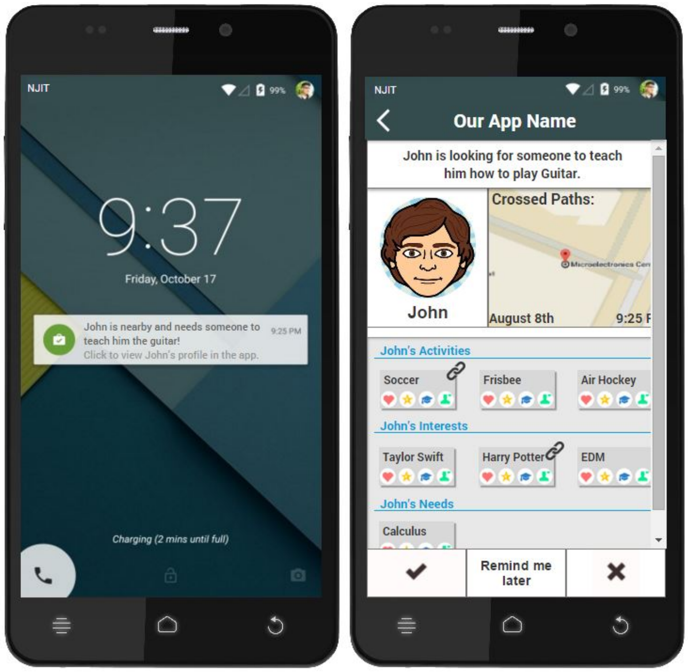


Figure 10.6 Early low-fidelity mockups of the match notification (left) and match screen (right).

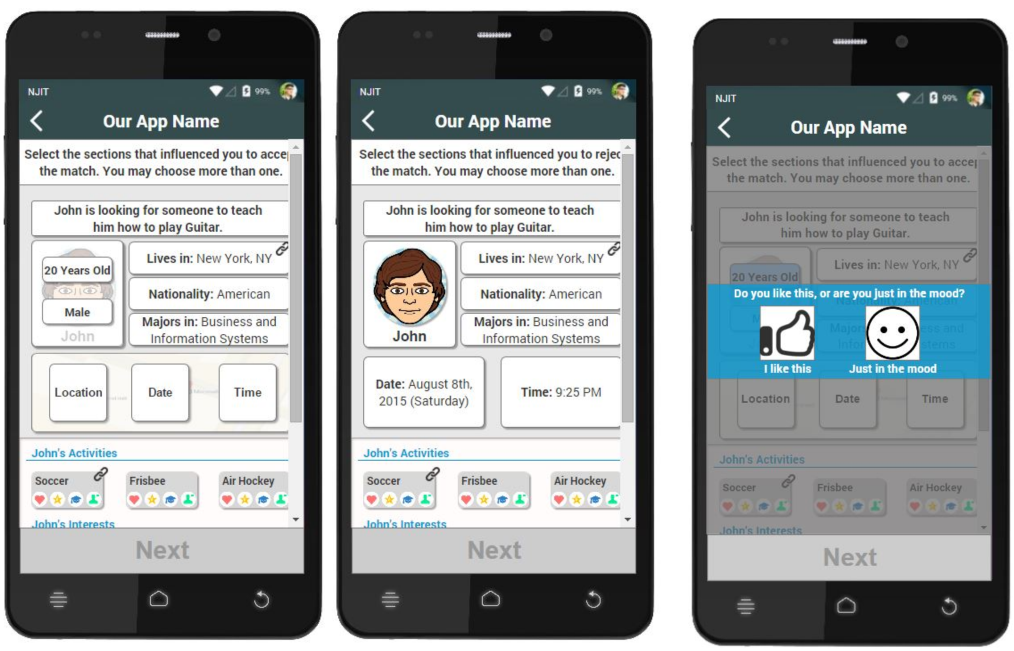


Figure 10.7 Early low-fidelity mockups of the feedback screens.

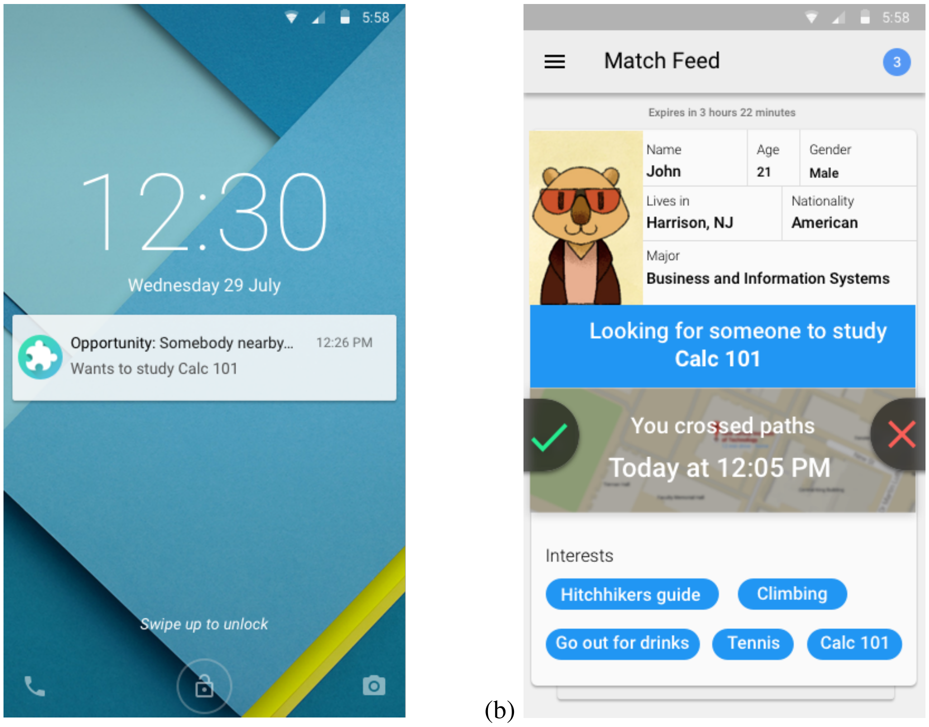
(a) (b)

Figure 10.8 Early low-fidelity mockups of the match screen (a) and feedback screen (b).

Note that at this stage we were not concerned about mediating the introduction process at the moment. Future work could include a simple chat / messaging feature, and explore further how the initial interaction between matched people could be mediated. We explored initial designs of additional features such as a match history and match preference settings, but postponed their implementation for future work since they are beyond the scope of the current work.

10.3.3 *Encount'r:* Application Design and Specifications

After numerous design iterations, we decided on a final version to be implemented as our first prototype *Encount'r*. The core part of the application is the "Ongoing Notification" (**Figure 10.9**.a), which informs users about relevant nearby encounter opportunities. Users can scan the notification text (e.g., "Opportunity: Somebody nearby wants to study Calc 101") at a glance to decide if the person sounds interesting or relevant (opportune relational context) and if they are currently in an opportune social and personal context to act on the opportunity (i.e., free and in the mood).



(a) (b)

Figure 10.9 Tapping on the Ongoing Notification (a) will take the user to the Match Screen (b).

(a) (b) (c) (d)

Figure 10.10 Examples of Ongoing Notification Updates over Time.

Whenever a new encounter opportunity nearby is detected, the ongoing notification is updated with the most recent and relevant opportunity. When opportunities ‘pile up’ over time, the notification contains a counter indicating how many encounter opportunities are currently nearby (**Figure 10.10**). Tapping on the notification takes the users to a detailed match profile, as shown in **Figure 10.9** (b), providing personal information about the matched person, such as their name, age, gender, current city, nationality, and major (as this was designed for college students). Moreover, the match profile highlights the notification text as reason for the match in the center of the screen.

The match screen also shows when the two matched users crossed paths, with a blurred map image and a timestamp. At the bottom of the page additional (not necessarily shared) interests of the matched person are listed. Users can either swipe right to 'like', or to swipe left to 'dislike' the match, which will take them to the feedback screen.

In order to avoid judgment based on people's appearance (what online dating apps like Tinder are known for), but instead turn users' attention to the profile attributes and shared interests and activities, we decided to include cartoon animal avatars instead of real profile pictures (**Figure 10.11**). We explored the impact of the profile avatar on people's decision in post-study interviews.

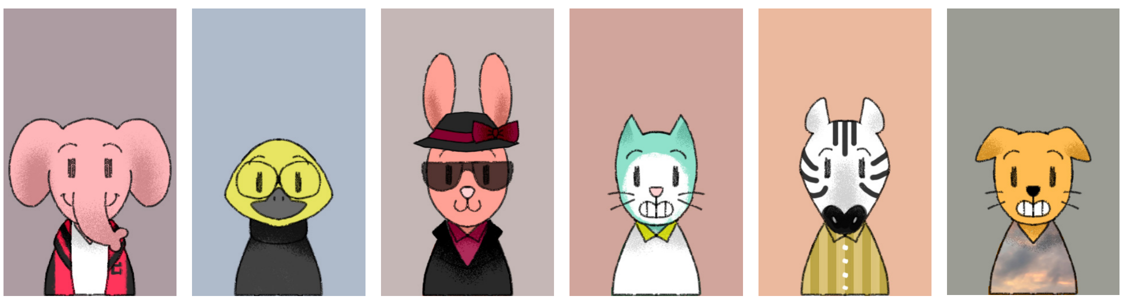
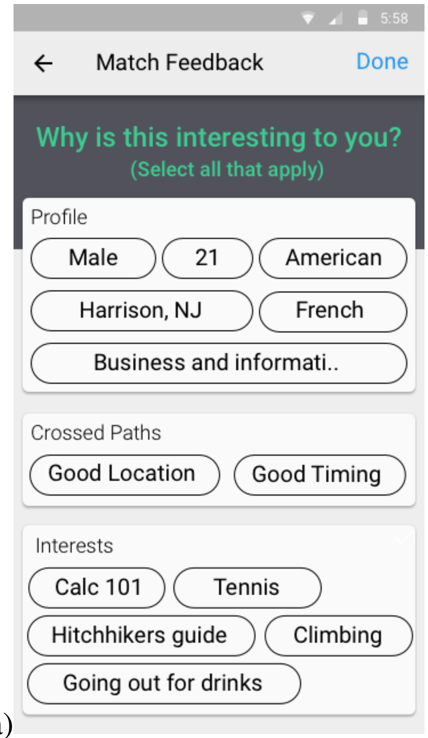
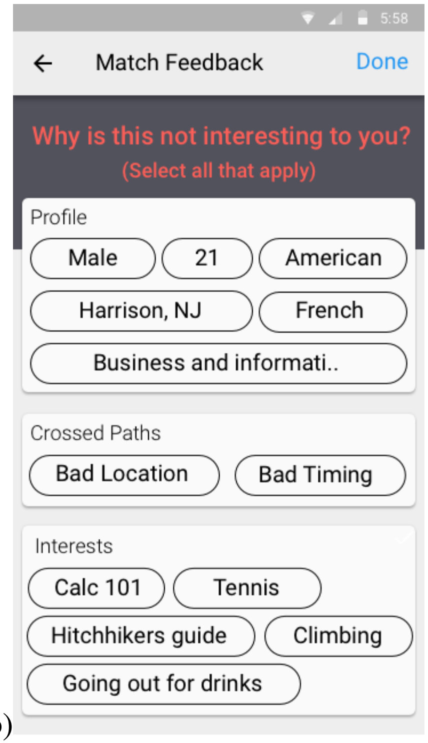


Figure 10.11 Examples of the animal cartoon avatars designed for the matching app.

The match feedback screen was designed to collect quick and easy feedback from users as to why a particular match was interesting or not interesting to them. On this screen, all the information bits on the match screen are turned into selectable buttons, which allows users to quickly highlight one or more reasons that made the match opportunity interesting (or uninteresting) to them (**Figure 10.12**). Moreover, users were able to select "good/bad timing" and "good/bad location" as feedback buttons.



(a)



(b)

Figure 10.12 Feedback screen after accepting (a) or rejecting (b) a match.

After submitting feedback, the user is taken back to the match feed. The match feed may contain a stack of matches that have not been acted upon yet, with the newest one always on top of the pile. In that case, after acting on the most recent match, the user is shown the second most recent match afterwards. If there are no more match opportunities nearby, the user will see a message saying “There are no new match opportunities at the moment. Check back again later.”

10.3.4 Preliminary Concept Evaluation

We evaluated both usability aspects and overall concept among target group representatives with 24 university students using a think-aloud protocol, which provided valuable insights into how to adjust the user interface slightly to improve people’s understanding of the app in preparation for our field study. We explored if people understood the concept of the app, what they found confusing or disliked, if the avatar influenced people’s decision, or triggered any negative feelings. Moreover, we wanted to understand how people made their decision (like or dislike) based on the information presented to them, as well as what were their reasons for liking or disliking a match. To recruit participants, we randomly asked students in the campus center of our university if they were willing to participate in a quick study for 10 minutes. Those who agreed were introduced to the idea of social matching and shown an interactive prototype that allowed users to like or dislike a match and provide feedback about their selection. We told participants to interact with the app while thinking aloud. The tested prototype did not yet include personalized matches, but 15 test matches with some examples listed in **Table 10.4**. We noted down their decisions (like/dislike) for each match and their feedback afterwards. In the end, we discussed their general thoughts about the app.

Table 10.4 Examples of Match Types & Reason-to-Match Strings

Match Type	**Reason-to-match**
<Passionate Interest>	*"Likes to watch Games of Thrones"*
<Skill Level>	*"Is also a beginner at sign language"*
<Willing to teach>	*"Looking for someone to teach Piano"*
<Rare Demo-graphic>	*"Is also Colombian"*

Overall, we received positive feedback. For example, P12 (m, 19) said *"I really like this idea, I would download it if it were only for students of this university."* In terms of avatars, P2 (f, 21) pointed out that they were an interesting idea: *"First, I missed a real picture, but thinking about it, it might be better [this way], because otherwise I'd just pay attention to the picture."* We saw that participants liked matches quite frequently (about 70% of the time). When asked why, a frequent response was *"I just like to meet new people around campus."* (P11, f, 24) Also, it was mentioned that "*rejection feels harsh.*" (P19, f, 23) Nevertheless, we have to carefully consider the limitations to the decisions in terms of truth and realism, because the evaluated matches were based on generic test data and not personal data. On the feedback screen, we saw that gender and age as well as other not-shared interests were often selected as reasons for disliking (e.g., *"I don't like* *anime*” P10, f, 20). Furthermore, after disliking someone, participants were worried if the other person would know they rejected them, which highlights that this process has to be designed with users’ privacy concerns in mind. People assumed that the app would learn from their feedback for future matches. Some other interesting ideas came up, e.g., one participant (P15, f, 19) wanted to be able to tap on an interest on the match screen to see more people with that particular interest, while another (P9, m, 23) wanted to be able to add an interest seen on match screen to his own profile.

The fact that the matches were not personalized limited this study, as well as the fact that we were only able to recruit people who were interested and willing to interact with us spontaneously. Yet, we gained valuable insights into how to adjust the user interface slightly to improve people’s understanding of the app in preparation for our field study.

10.3.5 Field Study

For our field study, we implemented above application design to run on Android smartphones. The goal of this field study was to evaluate our design artifacts and collect feedback about different match opportunities in the wild, in order to further validate our theoretical framework of opportunistic social matching. Instead of aiming to identify real encounter opportunities between study participants, we generated hypothetical match opportunities for each participant based on his/her profiling survey. This allowed us to conduct the field study without relying on real match opportunities to happen, which would have required a much bigger participant pool as well as a longer duration of the field study. Instead, we controlled that each participant was exposed to the same amount of opportunities over a time frame of five days. To generate personalized match opportunities, we used 20 different user attribute types that we collected in the profiling survey (Table 10.5). For each attribute type we generated a reason-to-match (r2m) string that was shown to the user on the match screen as well as in the notification (e.g., “Looking for somebody to study Calc 101” for need-based matches).

Table 10.5 Overview of Match Types and Reason-to-match String

DEMOGRAPHICS	
Nationality	*“also is <nationality>”*
Hometown	*“also is from <hometown>”*
Current city	*“also currently lives in <current_city>”*
Native language	*“also speaks <native_language>”*
Other language	*“also speaks <other_language>”*
SCHOOL & WORK	
Major	*“has the same major <major>”*
Campus organization	*“also is part of <campus_organization>”*
Work field	*“also works in <work_field>”*
INTERESTS & ACTIVITIES	
Interest	*“Likes <interest>”*
Activity	*“Likes <activity>”*
Unique interest	*“Likes <unique_interest>”*
Watch	*“Likes to watch <watch>”*
Game	*“Likes to play <games>”*
Try	*“Wants to try <try>”*
NEEDS & OFFERS	
Looking for	*“Is looking for someone for <looking_for>*
Willing to teach	*“Is looking for someone to teach them <attribute>”>*
SKILL LEVEL	
Learn / Improve	*“Is willing to teach <learn_improve>”*
Expert	*“Is an expert in <expert>”*
Beginner	*“Is a beginner at <beginner>”*

We invited undergraduate Android users that had filled out at least 16 of the 22 match types fields in the profiling survey and invited them to sign up for the field study, offering $20 incentive for successful participation. After signing up, they were scheduled for a 15-minute orientation session where we demonstrated the designs of our opportunistic social matching prototype, instructed them how to use the application for the next five days, and then installed the application on their phone.

In order to evaluate the concept of passive context-awareness, we triggered a large number of opportunities for each participant and update the ongoing notification quite regularly, and then use timestamps to analyze how often, when and with how much delay people were acting on matches. The prototype was programmed to trigger 30 encounter opportunities per day (between 7:00 AM – 10:00 PM), resulting in a new match opportunity every 20-40 minutes (at random times). Since the field study lasted for five days, every participant was exposed to 150 opportunities throughout the study. We instructed participants that while they had to be active in the application at least once per day, they did not have to act on all notifications, but when they were free and/or interested. We further informed participants that, since this was an early research prototype, not all of the matches they would see were real, but that they should act on all of them assuming they were real.

10.3.6 Post-study Interviews

In order to complement the quantitative field study data with qualitative feedback from participants, we conduced post-study interviews. In the interviews, we asked field study participants about their overall experience with using technology to meet new people, as well as how easy or hard they find it to meet new people on campus. Then, we delved deeper into their experience with using the application. We asked how often and why they looked at notifications, and how often and why they missed or ignored notifications. Further, we discussed which of the opportunities they liked and which ones they disliked, and why. We were also interested in hearing how they would like an in-person meeting to be coordinated and supported through the application, and what were their thoughts on having a cartoon animal avatar instead of a real picture. We ended the interview by asking what they liked most and what they liked least about the application, as well as things they would like to see added or changed. Moreover, we asked if they could see themselves using such an app in the future, and what benefits they would hope to get from it. In the end, we debriefed participants explaining to them that all of the matches they have seen were computer-generated matches and not real.

We invited all field study participants that successfully participated for five consecutive days for a post-study interview, offering an additional $10 incentive. Interviews were conduced in person, as well as over Skype video calling and were voice-recorded with the permission of the participant. We then transcribed and analyzed our data using qualitative content analysis for categorization and constant comparison, looking for themes revolving around our research questions as well as new emerging themes.

10.4 Profiling Survey Results

We recruited students over the course of September to November 2015 to fill out the profiling survey by visiting classes and seminars, sending out emails via university mailing lists, and snowball sampling. At the end of data collection, 401 participants had filled out our profiling survey. We had to remove 11 incomplete profiles that contained less than five attributes. The sample included 72.6% male respondents, which is consistent with the demographic distribution of the technology-oriented university at which the study was conducted. Participants' ages ranged from 18-55 (mean 20.87, SD=3.68, mode 18). Most participants were commuters (57.6%), full-time (95.3%) and undergraduate students (83.0%) with a variety of different majors, and from 32 different nationalities (26.9% US American, 27.4% Indian, 54.6% native language English). Further, 69.3% reported to be single, while 27.3% were in a relationship and 0.7% married (2.7% rather not say). 46.2% owned an Android smartphone.

10.4.1 Computing Attribute Rarity

We computed baseline rarity scores for all attributes based on our sample of 390 participants providing us with a total of 10,026 attributes. On average, each participant entered 25.78 attributes (SD=10.25). Rarity calculations were determined by using the *Python package Natural Language ToolKit*[24] to compute frequencies for all user attributes and then divided frequency of the attribute by our sample population size (n=390). Our goal was to classify text appropriately, for example an interest in 'watching soccer' is different than 'playing soccer', but an interest of 'skydiving' and 'sky diving' should be determined to be the same interest for the purpose of more meaningful rarity

[24] http://www.nltk.org/ (accessed Jan. 2016)

calculations. The latter example was easily accomplished by stripping off whitespace. If a user entered 'Sky Diving' and 'skydiving' we also had to ensure this would be considered the same term for the sake of calculating frequency distributions so lowercasing all terms before stripping whitespace accomplished both these things. Looking at the dataset of all {n} interests we noticed subtle variations that required more complicated text classification techniques to work for all cases. Some methods we looked into were lemmatization and stemming (Manning et al., 2008). Stemmers reduce a word to its morphological stem, for example 'skydiving' -> 'skydiv'. Stemmers are notorious for overcorrecting and can lead to specific problems for our extended use case. Stemmers chop the end of words off and operate in a rather crude fashion, whereas lemmatization attempts to reduce words to their dictionary root. Lemmatizers need a part of speech tag (noun, verb, adjective, adverb) in order to more accurately reduce words, and since we often lacked the proper context with which to use a lemmatizer, our efforts with them seemed to be in vain. Due to their complexity, we decided stemmers and lemmatizers were beyond the scope of the current study. However, we have evaluated these potentially more effective methods of conducting string similarity measures that we are hopeful we can implement in future work for more accurate data analysis.

Table 10.6. shows the mean rarity across attribute types. We see that on average, *other language* was the most common attribute in the survey (mean=0.089, SD=0.212), followed by *current city* (mean=0.049, SD=0.208) and *hometown* (mean=0.033, SD=0.153). The high standard deviations show that rarity varied strongly within attributes type. An overview of the top 10 most common attributes is shown in table **Table 10.7**. We can see that *English* as the native language is shared by 96.4% of our survey respondents. Moreover, 54.4% listed *soccer* as a game interest.

Table 10.6 Mean Rarity across Attribute Types

	N	Rarity Mean	Std. Deviation
Demographics			
Hometown	390	0.033	0.153
Current city	390	0.049	0.208
Nationality	390	0.013	0.043
Native language	390	0.007	0.009
Other language(s)	444	0.089	0.212
School & Work			
Campus organizations	193	0.009	0.009
Major	390	0.021	0.044
Work field	206	0.020	0.042
Interests & Activities			
Interest	783	0.008	0.018
Activity	774	0.030	0.066
Watch	1147	0.012	0.025
Games	749	0.012	0.034
Try	620	0.012	0.044
Unique interest	389	0.008	0.024
Offer & Needs			
Help	391	0.006	0.0146
Looking for	397	0.007	0.0159
Willing to teach	549	0.031	0.0666
Skills			
Beginner	400	0.012	0.0277
Learn / improve	505	0.011	0.0312
Expert	529	0.015	0.0363
Total	10026	0.018	0.0714

Table 10.7 Top Ten Most Common Attributes

Attribute	**Attribute Type**	**Rarity**
English	Native Language	0.964
Soccer	Games	0.544
Skydiving	Try	0.403
Newark	Current city	0.377
Basketball	Activity	0.372
Cooking	Expert	0.351
Newark	Hometown	0.346
Indian	Nationality	0.303
Football	Beginner	0.264
Hindi	Other Language	0.264

10.5 Field Study Results

A total of 38 undergraduate Android users signed up for the field study and were invited for a 15-minute orientation session to instruct them about study procedure and install the application on their phone. Nine of them did not show up for the orientation. We had to exclude three more people who stopped using the app before the end of the 5-day study. Furthermore, we removed data from one participant who consistently responded with "Like" to all of the matches they received. That left us with 25 successful field study participants between the ages 18 and 25 (mean=20.12, SD=1.90, mode=18). Eighteen participants identified themselves as "male" (70.2%), 6 as "female", and one as "other". 19 of them were single (76.010%) and six were in a relationship. Furthermore, 10 were commuters (40.0%), while 15 lived on campus (60.0%). We had a variety of nationalities (5 American, 5 Indian, and 15 other nationalities) and majors (including biology, business, electrical engineering, information systems) represented in our field study sample. The average sociability score of our participants ranged from 1.92 to 4.50 (mean=3.429, SD=0.524), representing a wide range of sociable personalities (1 being the least social, and 5 being the most social).

10.5.1 Descriptive Statistics

After cleaning the data, we were left with feedback on a total of 3211 matches from our 25 field study participants. On average, each participant had acted on 128.44 matches over the course of the study. Overall, 52.9% of matches (n=1698) were liked, while 47.1% were disliked.

Table 10.8 shows the frequency of match decision (liked vs. disliked) per match type. Since participants had entered different amounts of profile items, not every match type was generated with the same frequency. Looking at broader attribute categories, *school & work* matches were the most frequently liked (61.51%), while demographic matches were the least frequently liked (46.18%). Delving deeper, we can see that matches for a shared interest in a certain *game* were the most frequently liked (67.4%), followed by *campus organization* matches (66.2%) and matches for *watching sports or movies* (60.8%). The least frequently liked match types were for *help* (37.9%), shared *hometown* (43.0%), and *native language* matches (44.5%).

Table 10.8 Frequencies of Match Decision per Match Type

	LIKED		DISLIKED		TOTAL
	N	%	N	%	
Demographics	**375**	**46.18%**	**437**	**53.82%**	**812**
Current City	55	47.00%	62	53.00%	117
Hometown	153	43.00%	203	57.00%	356
Nationality	45	57.00%	34	43.00%	79
Native language	69	44.50%	86	55.50%	155
Other language(s)	53	50.50%	52	49.50%	105
School & Work	**147**	**61.51%**	**92**	**38.49%**	**239**
Campus organization	45	66.20%	23	33.80%	68
Work field	34	61.80%	21	38.20%	55
Major	68	58.60%	48	41.40%	116
Interests & Activities	**738**	**57.21%**	**552**	**42.79%**	**1290**
Interest	117	54.90%	96	45.10%	213
Activity	109	56.80%	83	43.20%	192
Watch	233	60.80%	150	39.20%	383
Games	126	67.40%	61	32.60%	187
Try	94	48.20%	101	51.80%	195
Unique interest	59	49.20%	61	50.80%	120
Offers & Needs	**183**	**47.41%**	**203**	**52.59%**	**386**
Looking for	66	47.50%	73	52.50%	139
Help	39	37.90%	64	62.10%	103
Willing to teach	78	54.20%	66	45.80%	144
Skill level	**255**	**52.69%**	**229**	**47.31%**	**484**
Beginner	64	50.40%	63	49.60%	127
Learn / Improve	72	54.10%	61	45.90%	133
Expert	119	53.10%	105	46.90%	224
TOTAL	1698	52.90%	1513	47.10%	3211

Table 10.9 Mean Response Delay, Rarity, and Passion Level Across Match Interest

	LIKED			DISLIKED			TOTAL		
	Mean	N	SD	Mean	N	SD	Mean	N	SD
Response delay (min)	105.23	1698	214.80	133.64	1513	237.28	118.62	3211	226.08
Attribute Rarity	0.1433	1698	0.2501	0.1976	1513	0.2953	0.1689	3211	0.2737
Attribute Passion	3.93	1341	0.96	3.75	1126	1.01	3.85	2467	0.99

Table 10.9 lists mean response time, rarity of the reason-to-match, and mean participant's passion level for the shared attribute the match was based on. Passion level was only collected for interests, not for demographics (hence, n=2467). Response time was 28.41 minutes faster when the match was liked (mean=105.23) than when the match was disliked (mean=133.64). Moreover, on average the shared attribute was rarer when

the match was liked (mean=14.33%) compared to attribute rarity when disliked (mean=19.76%). Participants were also more passionate about the shared attribute, when they liked that match (mean=3.93) than when they disliked it (mean= 3.85).

Table 10.10 and **Figure 10.13** show how frequent different match information details were selected as a reason for liking or not liking the match. Note that participants were able to select more than one field as reason for their decision. Overall, we see that one or more of the five *additional interests* of the matched person were the most frequently selected as reason for liking the match (n=1245, 73.32% of all liked matches), followed by the *reason-for-match* attribute (n=1228, 72.32%), and the match gender (n=526, 30.98%). Looking at which fields were most frequently selected after disliking a match, we see that *bad time* (55.77%), *additional interests* (36.57%), and *bad location* (36.57%) were the most frequently selected. The differences between how often the field was selected (vs. not selected) after liking versus not liking are significant for all feedback fields, except for good versus bad location (Pearson's Chi-Square listed in Table 10.10).

Table 10.10 Frequencies of Feedback Selection after Liking/Disliking the Match

	Reason for LIKE		Reason for DISLIKE			
	N	% of total liked (n=1698)	N	% of total disliked (n=1513)	Total N	Pearson χ^2
Relational Context						
Reason for match	1228	72.32%	79	4.65%	1307	1492.471 **
Personal / Social Context						
Good / bad location	367	21.61%	303	17.84%	670	1.221
Good / bad time	283	16.67%	947	55.77%	1230	714.021 **
Additional Info about Match						
Gender	526	30.98%	141	8.30%	667	228.048 **
Age	338	19.91%	235	13.84%	573	10.44 **
Hometown	137	8.07%	94	5.54%	231	4.126 *
Nationality	192	11.31%	54	3.18%	246	67.726 **
Additional interest(s)	1245	73.32%	621	36.57%	1878	377.484 **

** significant at p<0.05* *** significant at p<0.01*

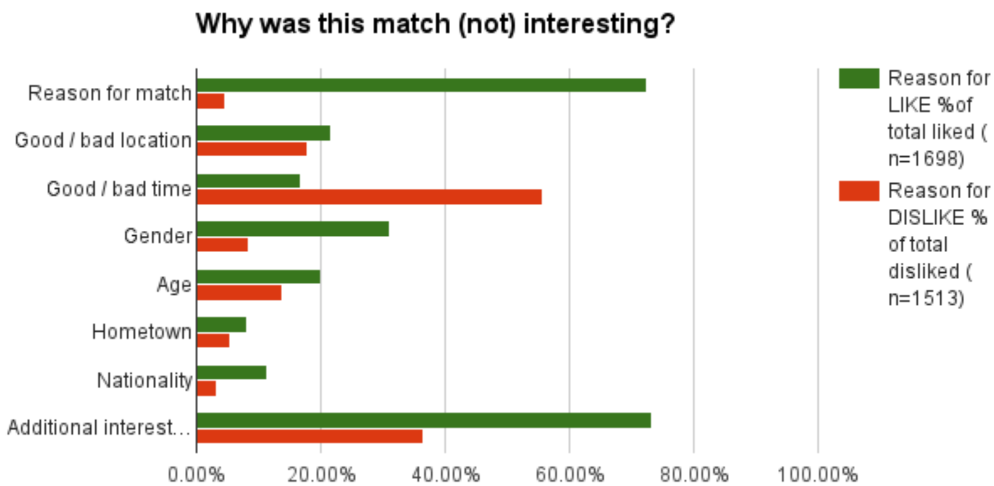


Figure 10.13 Frequencies of reasons for liking and disliking a match.

We further looked at how long it took participants to respond to match notification. On average, participants acted on a notification within 118.62 minutes (SD= 226.08) ranging from the quickest response time of 0.07 minutes (4.2 seconds) to the longest of 2170.97 minutes (more than 36 hours). **Figure 10.14** shows a distribution of the delays, highlighting that most notifications were acted upon within 2 hours. Delving deeper into the frequency distribution we found that about 75% of matches were responded to within 2 hours, 60% within 1 hour, and 50% within 33 minutes.

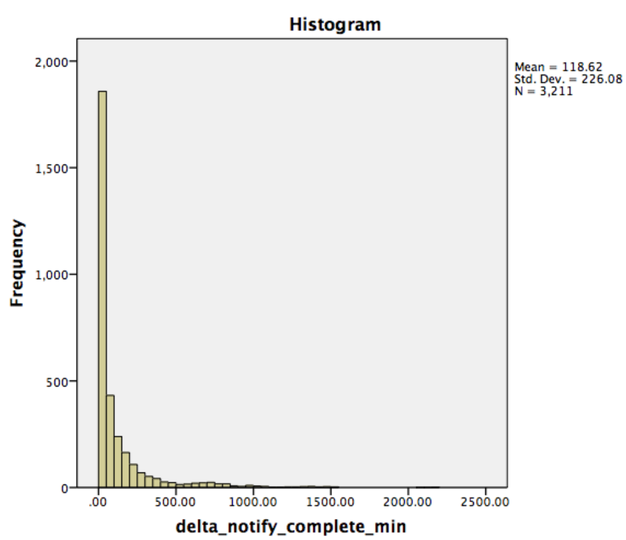


Figure 10.14 Frequencies of response times.

10.5.2 Hypotheses Testing

We tested our hypotheses using Pearson's Chi Square and non-parametric Mann Whitney U tests.

Testing H1: The match type (demographics vs. interest vs. need vs. skills) is associated with the acceptance of the encounter opportunity, we compared match interest across the broader attribute categories demographics vs. school & work vs. interests & activities vs. offers & needs vs. skills and found that differences were significant: Pearson χ^2=41.88 (df=4), p<0.001, supporting H_1.

For *H2: The rarity of shared attribute is positively associated with the acceptance of the encounter opportunity*, a Mann Whitney U test supports that attributes were significantly rarer when the match was liked: Mann Whitney U=1163095.5 (*p*<0.001).

Our hypothesis H3: How passionate a user is about the shared attribute is positively associated with the acceptance of the encounter opportunity, was also supported by a Mann Whitney U test showing that participants were significantly more passionate about the shared attribute when they liked that match: Mann Whitney U = 684088.0 (p<0.001).

Finally, *H4: The response delay is positively associated with the acceptance of the encounter opportunity,* was also supported. Participants responded significantly faster when liking the match than when disliking it: Mann Whitney U=1118789.0 (*p*<0.001).

10.6 Interview Findings

We interviewed 20 study participants (15 male, 5 female) within three days after they completed the field trial to get a better understanding of their user experience with *Enocunt'r*. Interviews lasted between 23-38 minutes. Below, we present our key findings related to our research questions together with representative quotes. Participant names have been changed to preserve their anonymity.

10.6.1 Overall User Experience

Overall, our participants reported having had a positive experience testing the Encount'r app: *"I thought it's a great idea, it's really interesting."* (Andrew, m, 20) Participants found the application quick and easy to use. *"It was pretty good because it was very simple. […] It was just punching a few buttons. I was actually looking forward to it. So when the notifications came in, I was like, Oh let me see. So I looked frequently at the app."* (Margret, f, 20) Daniel (m, 18) described how he first was skeptical about the *Encount'r* app but enjoyed it later: *"At first I was like, what is this all about. And as it kept going, I started to really get into it a little more, I was like, this is pretty cool, I like this, I could really see myself using it down the road, and telling friends about it."* Tina (f, 19) told us that as her friends saw her using the app, they were curious and wanted to know more *"Some of my friends saw me using the app, and they were like, where can I download this. And I was like, you can't yet. But I think once you guys release it, it's gonna be a lot of people, it's gonna explode, like that dating one, that I forgot what it's called."*

When we asked what kind of benefits participants could see getting from the using the *Enocunt'r* application in the future, numerous participants told us about how it is harder to make friends in college after the initial socializing phase: *"In the beginning [making friends] is really easy, but then it becomes hard. In the beginning everyone is seeking new friends, so everyone is open, everyone talks to each other and stuff, but after the first couple of weeks everyone has their groups, so then meeting new people is hard. Because you meet new people through class, now those people are in your class already. And because everybody has formed their groups, that's who they talk to, so it gets like harder as you progress."* (Andrew) Based on similar stories, participants agreed that *Encount'r* could help them to get more friends in an environment where is sometimes can be hard to meet new people. *"I think an app like that might help to get to know someone in your class better, or someone around campus, because that can be very intimidating* *when you're on campus with like 40,000 other people, and you feel like a nobody in your school. But with an app like that, you could feel like you're not a nobody, you could get more friends, people that like the stuff, do the same stuff as you do, it would definitely help people, big time."* (Daniel)

Kim (f, 22) further elaborated that it can be particularly hard to find people with certain common interests: *"I liked the fact that they match you based on common interests because maybe you have a hard time finding people in your own life that has that same common interest."* Keith (m, 19) told us about the same problem: *"Finding more friends that like the same stuff as me, without having to awkwardly talk to them in an elevator or have to wear a band shirt. Because I've had people come to me, where I would wear a band shirt and people would be like "Oh, you like that?" And that's a good thing, but this is more oh you're walking past someone, *beep* "They like 'The Killers'."*

Participants described numerous cases where they would like to meet new people, mainly things related to on-campus activities. *"I've seen on some message boards people have a hard time meeting people on campus so this app is a great way to do that. For on campus activities, I guess going to the game room downstairs to play pool, if someone wants to play piano in the campus center, meeting up at the pub, or something or studying for a class."* (Scott) Lindsay (f, 21) describes how she sees the app helping commuters in particular: *"I think it's a really cool concept, I think it could really help out a lot of people, I'm sure I'm not the only commuter on campus who has trouble meeting people. I can actually see a use for this for my friends who are just as socially awkward as me."* Moreover, Austin saw the app being useful for professional networking: *"[The app] would be good for networking, so you have that not only for a social aspect, but career progressing as well, like professional aspects that would be interesting. Especially on campus if more people were my major if I didn't know them it would be great to know to see what they are up to and interested in."* (Austin, 21)

10.6.2 Relational Context

When we discussed with participants what kind of matches (*relational context)* were the most interesting to them, we heard again that rare shared interests or demographics elicited the most excitement. Keith explains: *"I saw like a very obscure game I listed as my thing and I was like oh wow that's pretty interesting."* In particular, we heard numerous stories about matches for rare shared demographics, such as nationality or hometown, which excited users. Lindsay, who has roots in Lithuania, tells us, *"Occasionally I paid attention to nationality, when it was like "oh this person is also Lithuanian", that caught my attention."* Natalie (f, 24) describes a similar attitude towards rare shared nationality matches: *"I'm from Barbados so things would come up, this person is from Barbados and I thought that was pretty cool, because there are not many people from Barbados on this campus."* Moreover, Alex (m, 20) explains that seeing matches based on his rare hometown combined with his same major excited him the most: *"There were some that were not only my hometown but also the same major. And I was like 'No way!' […] Because like, my major is kinda common, but not my hometown. I don't know how they both have it. It's too rare."* However, Alex also made an interesting point, saying that rare demographics matches are very exciting to see, but he does not expect much from them. In his opinions, matches for playing video games were more valuable, even though that interest is much more common: *"Maybe it's just because of my hometown, but for that's a really cool factor, because I very rarely meet people from where I grew up from. So I'm like extremely biased. 'You're from [my hometown], absolutely! Who are you? I don't know, but maybe I know you'. I'm very excited. However, the only difference is that, I mean realistically I don't expect that much out of it. I'm doing it to entertain myself. Because when I see [my hometown], I wanna meet this person. But the [video game] matches were much more reasonable in my opinion, that's actually an extremely popular game, so I take it a significant percentage at NJIT would play that."*

Moreover, we heard again that it is not only about contextual rarity but also about rarity in their current social network (i.e., circle of friends). Simon (m, 21) describes how certain shared demographic might be common around him, while he does not know any of them in person: *"A big one for me was when I got one that was, this person is also Hindu, this person speaks Gujarati, that's my background. I mean I see Indian people all the time but I don't interact with them much because I don't know anything about them. I can't just go up and start talking to them. So it's easier to know that people, those kind of people exist. That was a big hit for, knowing that there are people out there with the same background, same interests. If the chat was available at that time, I definitely would have started talking to them, and learn more about them."*

On the other side, several participants told us that they did not pay attention to the match's nationality on the profile if it was not shared: "*I thought the nationality was not as useful. I was like, well I'm not gonna say NO because somebody was Canadian. And to me, I probably wouldn't wanna meet up with you for the only reason that you are Egyptian, I never really used that one."* (Alex) Moreover, people felt almost offended by the option to say the match was *not* interesting because of the nationality: *"It felt a little weird, showing the nationality as one of the interesting or not interesting things because I felt like, I honestly felt a bit racist if I picked something like that, so I always avoided clicking something like that."* (Keith)

Furthermore, our interviews underlined the finding that passion levels play a big role, as Daniel explained: "*The biggest one for me was the 'Fresh Prince of Bel-Air", I love that show. When I saw that someone liked that I was like 'checkmark'."* Along the same line, Tina told us, *"I'm big on horror movies. Some people were like, love horror movies, and I was like, why don't we do something with horror movies. It was just really cool to see that."* We also saw that a lack of passion for and/or lack of rarity of a commonly liked TV show can have the opposite effect*: "I guess watching a specific TV show, for me that's not really something … everybody does it. That one show, I know* *everybody watches it. I'm not gonna meet this person just to watch TV with them."* (Simon)

Another type of match people regularly described as desirable was about doing activities together: *"There were some that were about going out and actually doing stuff, that's the ones that were interesting*." (Simon) For example, Tina would like to meet people to play video games: *"I'm really interested in competitive video games, the game I play is Super Smash Brothers, and a lot of people play that on campus and I kept getting matches, super smash brothers in common, and I was like, this is so cool, find new people to play with. I totally wanna message them on the app, come play with us whenever you want."* Similarly, Lindsay describes: *"I think the one's I said yes the most to were people who were looking for people to play tabletop games with. That's a really big thing for me […] so I paid more attention to that."*

Furthermore, for activity matches participants took into account how easily the activity could be organized in the near future: *"Like watch football, that would be something in my opinion that wouldn't be too hard to just meet up and let's watch football. Or 'playing league of legends', those things are in my opinion a little simpler to setup, just like 'Hey let's play'. Some of the other ones were a little impossible. Like it would be a little hard to do skydiving now." (*Alex)

Trying new things was also repeatedly mentioned as something very interesting to people: *"I mostly selected the things that I've never done but wanted to try. So things like skydiving, I've never done that, but I'm interested in doing that. Or like programming, developing Android apps, never done that, but wanted to."* (Simon) Another case where this was brought up was for teaching something new: *"I did pay attention to "willing to teach French", I've been trying to do that for a while now. There were a couple of times people were looking for people to road trip with, which was really, really exciting for me. Yeah I would love to do that, maybe not with a total stranger [laughs], you know get coffee a few times and the drive to California."*

*(*Lindsay)

Another repeating theme was about the desirability of matches for need-based and school-related matches, and therefore referred to by Simon as *necessary*: *"A lot of them were for like studying or help with EC class, so I wouldn't say that's interesting to me, but it's necessary, to have somebody to study with, to work with. It was good to find somebody for that."* Tina told us, *"I really like the fact that I can find someone that is studying for the same exam as I am. Because usually I post on Facebook, 'Hey, is anyone studying for this exam?' and with this app, […] I could put in [the app] that I'm looking for somebody to help me with that class, and then I could match with people just by walking by them on campus."* The contextual rarity of a need related to a school-based shared attribute is relevant here, too, as Natalie told us, *"I liked that it told you what people's major is, because if you're looking for someone to study with, you know, I'm a biochemistry major, and there are not much of us on campus either, […] before I only met like one other person*."

When we asked participants what they paid attention to most when making their decision, apart from the shared attributes, they often mentioned age and gender. For certain activities, like playing soccer, male participants preferred being matched with other males: *"In certain things like with soccer players, it's not like I'm against female soccer players but it's not the same type of game."* (Austin)

In some cases participants seem to have romantic motivations: *"I was like in the campus center and I was like 'sure', I mean to be fair, she was female and 18, that probably also added a factor. "* (Alex, m, 18) However, several of the male participants mentioned to prefer female matches, even when they were in a relationship, as for example Keith, who stated to be in a relationship, *"I did notice I was interested in more girls, there are not a lot of girls at NJIT and I like having more girl friends than guy friends so it's more about that."* Here, contextual rarity of being female at a technology-oriented university might play a role: *"There are already a ton of guys at NJIT, I figured*

I'd make some more female friends." (Daniel) At the same time, female participants also preferred female matches. A female participant explained, *"I probably liked more females. It was just, some of the profiles for guys were weird, and I just feel like the guys had different interests than me."* (Margret)

As expected, age was important and most participants preferred meeting people within their own age group: *"I saw a couple of people, like 25, 26, 28, and that was kinda old because I'm only 18."* (Daniel)*"If they were above 4 years older than me, I would immediately say no to that. "* (Keith)

As in prior work, we hear about interesting interactions between different relational and situational factors influencing people's interest in an encounter opportunity. For example, sharing something rare of something needed can overwrite age and gender preferences. Alex describes how a very interesting or valuable commonality as well as his preference for female matches trumps his age bracket preference: "*For the guys, if they were over like 22, just because, I'm 20 years myself, so just because they were over 22 I was very likely to hit NO, unless there was something I really liked, they were an asset in some way, they were interesting, or we had something cool in common. I remember there was some really old guy but he was from the same hometown as me, and I come from a very small hometown, so I was like, wow yeah, let's meet this guy. But as for the women, I did say yes to a lot of them."* (Alex) Similarly, some shared attributes – mostly demographic info – seem to mediate relational context: *"If the only common thing we have was that we speak the same language that would be kinda weird. But if we have other interests in common and we also speak the same language that'd be pretty cool."* (Henry) Daniel's quote below further highlights how passion could trump bad timing: *"A couple of times, it was bad timing, I was in class, or I was at work. [...] A couple of times I said it was ok, for things like Chicago Fire, I said it was ok even when in class because I love that show."*

As in previous work, it was the "right" combination of the social and relational context that led to most excitement about the encounter opportunity. An example of such a case came from Simon: *"Yesterday, I think, I got 'lifting weights' and I was in the gym, so that was like perfect. Good timing, let's go."* Tina had a similar story to tell: *"There was actually a good time, I had an exam last Wednesday, and crossed somebody looking to study for that class, and I was like, this would have been perfect, because I was studying for the class and they must have been walking by the lounge that I was in, and I was like, oh I totally wanna match with this person, if it were active right now, that was really cool. And it actually happened twice. I was doing homework for that class, and it said, this person is willing to tutor IT 101 and I'm working on that project right now, and he could have helped."*

10.6.3 Attending To and Ignoring Match Notifications

When discussing the design of the match notifications, numerous participants reported attending to their phone's notifications almost immediately most of the time, which is why they also responded to match notifications in a very timely manner. *"My phone would vibrate when I got a match and, just like when my phone vibrates for email and text, I would always take it out, and usually, with the exception of when I'm sleeping, I would be answering them as I get them."* (Andrew) Most of our participants described a similar habit like Daniel: "*I usually looked at them right when they came in, I never really waited. The longest I waited was maybe an hour, because I took a nap. And when they stacked up I went through all of them right away. I thought it was pretty cool, I want to do this now, I don't wanna wait."*

We received positive feedback about the hint text providing a preview of the reason for match. Alex pointed out: *"It was interesting that it actually gave you a little info, like, somebody's willing to fish. It said something specific; it wasn't just like "you have a match". I'm happy that it at least gave me a little heads-up because I was like, uh, that's a new one, so I went in with like a new interest. [...] This information I feel really helped. Because if I got the same little message, like 'you have a match', I would be like,* *kinda annoyed by that, because it just, it doesn't really help me rather than just continually grabbing my attention. […] because it gave me an idea, it was funny that I got to compare what I thought this person would be like with what they actually are."*

Furthermore, participants reported enjoying receipt of a match notification, providing them with a form of gratification. *"It was pretty cool. Every time I saw the little puzzle piece pop up, I was like Uooh, someone, I have a match, that was pretty cool. At first I wasn't sure, […] but as I started to use it, oh it's pretty cool, I really enjoyed it*." (Patrick, m, 19) Based on the interviews, we found that the immediacy of being informed about an encounter opportunity that was relevant to them right there and then was exciting people. "*I was in church yesterday and I saw a couple of matches, and I was like, uuh, fresh print, I was just sitting there, oh this is cool."* (Daniel)

When asking participants in what kind of situations they most frequently found themselves using the app, most people mentioned free time between classes, like Austin explains when he used the app most: *"So mostly like in between classes I would say is the biggest time."* Commuters also mentioned that during their commute by train or bus they found themselves using the app more frequently: *"I probably looked at it more when I was waiting for the bus."* (Kim) *"I take the train back and forth from New York City, so I use it a lot on the train because it's a good 40-minute ride*." (Austin)

Moreover, we heard that being alone triggered using the app and increased interest in encounter opportunities: *"I feel like I used the app more when I was sitting by myself, trying to see what other people were doing. I wanted to see what other people were interested in. […] Usually when I was alone, or when I was completely bored out of my mind, I was just like, let me see what's going on. And maybe someone is interested in doing something right now."* (Simon) Similarly, Alex told us, *"I remember I was in the food court, and I was like, oh I got a match, and I was like, oh that would be cool if they came and sat with me, because I was eating alone*."

Consistent with prior work, being busy was one of the most prominent reasons for ignoring match opportunities: *"It was just if I was busy I didn't look at it. At work, or sometimes you get caught up, like now I have two papers to write, so if I'm doing that I try to not look at my phone. Times like those [...] then I just clicked 'bad timing'."* (Andrew) When notifications arrived at an inopportune moment, participants reported intentionally delaying their response until a better time: *"So even if I was at work I wouldn't say I didn't like the person and then say 'bad location' or 'bad timing'. I would just wait till later when I had a chance to answer and then answer it."* (Henry, m, 18)

In other cases, participants used the 'good/bad location/time' feedback buttons to describe situations that were inopportune to meet someone. For example, Simon considered late-night matches for school-related activities as 'bad timing': *"Sometimes I looked at matches at 10 o'clock at night, I'm not gonna study with you right now."* Moreover, being in class was regularly mentioned as a bad location for an encounter opportunity *"Definitely I was looking at it sometimes in class, and I was like, I can't meet right now […] it was a bad location."* (Andrew)

An interesting issue that was brought up by Austin highlights how being in transit made anchoring the match to a certain location problematic: *"When I'm passing by on the train or in class that's not a good time.* […] *I would get matches when I am on the train but I would be living 30 minutes away, and working in New York which is another 40 minutes from Elizabeth and it would make no sense. So like geographical location would be the biggest reason for rejecting."* Alex experienced a similar problem: *"I was driving in a car and I got a match. And I was like, well, I have to say NO, because I'm moving, you'll never be able to find me."*

In our prototype, participants were not able to dismiss a notification. They had to act on it (like or dislike) and provide feedback in order for the notification to go away. We intentionally designed it that way to motivate participants to act on as many opportunities as possible. On one side, participants acknowledged that having the notification always on the lock screen could be beneficial: *"I did try to swipe it away, but* *it didn't come off my home screen, which is good. You actually had to look at it. And obviously it's always good to have the notification, unless people would never check the app. And that's why I made sure to look at it, because otherwise I wouldn't get it off my lock screen. For an app like this it's good to have notifications. Honestly, people like that the app interacts with them, they wanna know that they are getting matches, […] it's like gratification, you get a notification from somebody, that's good." (*Simon)

On the other hand, participants also criticized this feature repeatedly, as they did not want to be forced to make a decision on every encounter opportunity: *"Today, I was in the lab and I was doing all my lab work, so I had like 15 or so [new notifications] and then I went through them all. […] I didn't like that if you didn't respond to it at the moment, you still had to go through it, or at least you didn't have to but it bugged me that the notification was still there. So I went through it, even though..."* (Andrew) Kim had a similar experience: *"Sometimes it was slightly annoying because they would pile up and there was nothing else you could do than hit accept or reject. […] It shouldn't be a accept or reject and give feedback. Just an 'x-out' of it, so you wouldn't have to do it if you don't feel like it."* This was often due to the fact that participants found it hard to specify what exactly made the match interesting or uninteresting to them, as Lindsay described: *"There were times I didn't like the match but I couldn't quite figure out why. So I was like I have to give some sort of reason, so I'm going to pick, it felt almost arbitrary, it felt like I was cheating a bit."* Moreover, participants pointed out that opportunities were not relevant anymore after a certain time: "*I didn't have my phone with me until 7pm, there was an app request at like 12pm, I still had to go through it, but obviously we didn't cross paths, it was 7 hours ago, there was no point now. […] There should be maybe like a 15 minute period, after that the request goes away. Because otherwise you know, there's no real point. […] You know 15 minutes later that's no longer relevant, so either swipe away or it goes away naturally." (*Andrew) Lindsay described a similar scenario: *"With all of [the notifications] piling up, I might go back to someone that I matched with 12* *hours ago, so the time or location doesn't really matter anymore.*"

In regards to the amount of notifications (set to 30 per day in our study), several participants agreed with Andrew's quote: *"The amount of notifications I guess was a little overwhelming. You know sometimes it was one after another after another. And so maybe there should be a user preference, how many do you want in a day. Maybe some people only want 4 or 5, some want as many as they match with."*

Keith suggested that he would like to be able to mute the application for certain time frames: *"Well, I couldn't get rid of the notifications at the top by swiping. So it kind of forced me to look at the people, but first thing in the morning I'd see 6 [matches] and I would go [sigh]. I wish I could mute it for a little, like say okay I'm not wanting to interact with people, so I would most likely say not interested for a lot of people."* Henry voiced a very similar request: *"Whenever I had a notification I felt the urge to answer it. So I wish there was like a way to silence it for a few hours. At work […] if I could just disable push notifications for a few hours at a time that would be great. Or when you're driving. […] If you could be like say "I'm free from this time to this time, so you get most notifications during that time. So then you could message with people who are free during that time."*

Scott suggested to add a timing preference setting in the application: *"I would say, if I'm on campus then yeah, the notifications should keep popping up consistently, or maybe you could put something in, where you could put your time and availability, and within that range if would give you notifications."* Similarly, Kim requests, *"For the timing, I'm thinking you could set preferences in your profile. If you match with someone nearby and it's in that time but you don't want to meet anybody, you either aren't really sent the notification, or I don't really wanna say, it's saved for later?"*

10.6.4 Crossed Paths

In our prototype participants were not able to see the actual location of the encounter opportunity, but a blurred map image and a time stamp. This was partially because the prototype was not actually location-aware, but it is planned for a future location-aware version to preserve users' anonymity and avoid stalking and privacy compromises.

During interviews, several participants mentioned that the "crossed paths" information was very valuable to them. Tina told us how it helped her to determine if the opportunity was timely or not: "*I really like how it showed a map, and said, you met at this location and time, but sometime I was in class and it said you crossed someone just now, and I'd be like, oh they must have just walked by outside the classroom, so that would be a bad time. And sometimes when I walked over campus and crossed someone and then go back to my dorm to do nothing; that was always a good time.* "

Moreover, participants would like to see if they had repeatedly crossed paths with someone: *"Maybe if it's like repeated, like, oh you passed this person like 5 times in the past 4 days then clearly you're somewhat similar in schedule."* (Henry)

However, this feature also caused some confusion, Alex told us a story: *"When I left campus briefly and I came back, what happened was, you know the little location, the blurred map, you were around this area, I didn't know where it was. It no longer was actually where I was, maybe because Google maps didn't know where I was because it was a little remote, so it was interesting, because I was like, I don't know where this match is, and I don't know if this actually understands my location."* Kim described a similar problem when she looked at opportunities that happened some time ago: *"I never look at the notification right when I get it. So I don't really know where their location was, where we were near each other."*

We also learned that it is important to users to know how far away the matched person is to estimate how much effort a meeting would require: *"I wish it would say like this person is this many miles away, or like 100 feet away, a thousand feet away, a quarter of a mile away, […] because then I would have been able to gage, well I don't have a car, but I'm on NJIT campus, I could like walk 50 feet and then you go see someone. But at the same time, it kinda, oh they are 3 miles away, that's too far." (*Alex)

10.6.5 Profile Avatar versus Real Picture

As described earlier, we intentionally used cartoon avatars as match profile pictures in order to shift focus away from physical appearance to profile attributes. When we asked participants about their thoughts about the profile avatars, feedback was mixed. Some participants liked them but assumed they were placeholders for real images: *"They were cute. I assume when you turn this into a finished project […] you would replace that with an actual profile picture?"*(Lindsay) However, Lindsay and several other participants recognized not having a real picture as an advantage *"Not looking at someone's face, is an interesting concept, because you're not looking at the way they appear, you're looking at who they are, more so. I thought that was pretty cool actually."* Along the same lines, Alex described how the lack of a real picture made him more comfortable with the app because it felt less real: *"I feel like it was less serious or real, so you're dancing on the line, oh well you don't have to worry because it's just a duck. I didn't feel… what's the word? I didn't feel afraid, or not threatened, I was comfortable […] I like how simple and innocent it is, as I said. In some ways it's best not to know. You know, you're happily saying, oh wow, we have this much in common, I'm gonna judge from there."*

When further probing if they could see the app working without real pictures, most participants agreed that activity- or need-based matches do not necessarily need real pictures while romantic matches rely strongly on real pictures: *"Without pictures it could work, for certain interests like soccer players, I don't care what you look like but if we are going to go out for a movie that makes way more of a difference. But I would say yeah it would work like if you're in my major, it's your knowledge that matters, so I would say in certain cases it definitely wouldn't matter."* (Austin) On the other hand, Simon suggested to add activity-specific pictures, "*Maybe they can put in pictures of them doing an activity they're interested, like skydiving, you could see, oh they actually did it. They might have a lot to say about it."*

Daniel, as others, had a similar opinion about the advantage of *not* having real pictures: *"I think the avatar was cool because some people might discriminate if they see a picture, so I think the avatar might be better in certain situations. But if somebody is only looking for a girlfriend or boyfriend, maybe a picture would be better, but I think it depends on what you're on there for."*

When asking if they could imagine meeting someone without having seen their picture, we again had mixed findings. Lindsay for example said, *"I would rather see their face before going to meet up with them, yeah. Maybe in the chat feature, I could send you my picture*." Kim suggests a similar approach to profile pictures, *"I think once you say yes and they say yes you should be able to see a picture. When you're first choosing yes or no, I think the avatar is good. But once you choose yes I think it would be good to actually see the person. Because you gotta know who you're meeting."*

10.6.6 Proposed Features

During interviews, participants repeatedly described additional features that they would like to see implemented in the application. For example, participants assumed that the application would learn from their feedback: *"You can select what you like and don't like, and them I'm sure that the algorithm changes, you keep rejecting that kind of attribute, I'm gonna stop showing that kind of attribute."* (Andrew) However, our prototype did not have this implemented yet, which frustrated some participants: *"As I was checking off things that I didn't like, it would keep popping up with the same things that I don't like."* (Tina) As for several other participants, Tina wanted to be able to blacklist certain traits or interests she saw on profiles and for which she never wanted to receive a match in the future. Tina elaborates on this idea: *"I think you should be able to blacklist like a specific trait or something. Because a big turn-off for me is smoking or doing drugs and I saw people that I was matching that put that, and I was like, I don't wanna see those people at all."* Kim had similarly specific criteria for disliking matches: *"One person, I know for a fact, said smoking, and that's the only thing I pressed for dislike, even though we had stuff in common. And then they had like outdoors stuff, like* *hiking, and weightlifting, and I'm not really into that. […] Maybe in your preference, make a list of things that you are definitely NOT interested. So that even if you have a common interest with that person, if they just do that one specific thing, they won't notify you."*

In terms of giving feedback, Austin also would like to be able to like and dislike things on a certain match profile: *"So you like one person, like 90 percent but you hate one thing, so you don't want to meet them. The app wouldn't know that until you have that nit-picking."*

Our early prototype did not allow participants to chat with one another. This was an often mentioned as a drawback and much asked-for added feature: *"If you'd have the chat when I was testing it, it would have been so much more fun, more interactive, you could have discussed things. Because when I went through it, after you hit done, it was just, oh whatever. If we got a chance to talk to them it would have been a whole different experience."* (Simon)

When we asked our interviewees about actually meeting people from the app in person, most were very positive about that. However, scheduling was one of the most frequently mentioned challenges: *"It really depends honestly, I'm not on campus all the time, some days I'm on campus for longer than other days, so it would really depend, like if I get a match, and Wednesday I don't come to campus on Wednesdays, I don't have classes so, but I might be interested in getting lunch with them on Thursday or Friday, or something. But if it's Tuesday, and I have this 4-hour gap in between my classes, and I'm just sitting here, twiddling my thumbs, then that would be cool. " (*Lindsay)

Alex described his ideas for a future application feature to mediate in-person meetings in the following way: *"In the app there should be something like "Yes I wanna meet this person" and then "When? In 15 minutes? 30 minutes? An hour? Tomorrow?" Like I do not believe that you'd say 'Hey let's meet up' and then it would point me in the direction. I know me personally, I would just brush my teeth, I would just need 15* *minutes."* Scott also envisions *Encount'r* to provide meeting coordination tools: *"I guess you would have to put in an option, if we both match with each other, then we could say we want to meet, then we could pick a location and time, like Campus Center, or pizzeria, or something like that, put in a room number, and find a place, that's it."* Moreover, Daniel suggested that activity-based matches could already point to a nearby location where the activity could be done, like a park or gym: *"For the sports ones, like football or basketball, you could go to the park or go the gym and meet up with them and do that with them. I had a couple of those matches and thought oh that's cool, I'd love to go play football with them. Sports are maybe a little more relevant to meet in person that like a TV show."*

Some interview participants mentioned safety concerns when it comes to meeting in person and suggested incorporating some kind of verification to make sure people are trustworthy: *"If there's a way to say that all these people are real, then maybe meeting is ok. If they're all NJIT students, then ok, that makes sense, then they not gonna kill me. You know there's no sense of threat. We didn't share any personal information, they not gonna stalk me. So I guess if you verify that and say you can only sign in with a dot-edu email."* (Andrew)

10.7 Discussion

In this section, we discuss our field study and interview findings in regards to (1) operationalizing relational context, (2) passive context-awareness for opportunistic social matching, and (3) and other lessons learned from the research through design.

10.7.1 Operationalizing Relational Context

One goal of this study was to further validate previously explored methods to operationalize relational context based on attribute rarity, activity skill level, learning/teaching needs and offers (RQ1).

Analyzing users' feedback showed that the *reason-for-match* and other *additional* *interests* of the matched person (i.e., the relational context) were most often the reason for liking the match. On the other hand, *bad timing* and *bad location* were the most often reasons for disliking a match. From this, we conclude that relational context is more predictive of liking a match, while personal context (such as time and location) is more frequently a reason for disliking a match.

The profiling survey successfully allowed us to collect a large number of relevant attributes as well as users' passion levels. From the field study data analysis, we learned that computed rarity (within the defined community of a university campus) was associated with participants' match interest. On average, the shared attribute was rarer when the match was liked compared to attribute rarity when disliked (supporting H2). Participants were also more passionate about the shared attribute, when they liked that match than when they disliked it (supporting H3). Moreover, our data analysis showed that interest in a match was significantly different across the match types (demographics vs. interest vs. need vs. skills), highlighting that *school & work* matches were the most frequently liked, while demographic matches were the least frequently liked. In particular, matches for a shared interest in a certain *game*, *campus organization* and for *watching sports or movies* were most popular amongst field study participants. Based on this finding, we propose to put higher priority on these types of attributes, for example using weighted scores representing the importance of the attribute type.

Interview findings further highlighted once again how relational context should incorporate contextual rarity of and users' passion level for shared attributes. Moreover, for activities that can be done together, relational context should include meta-data about users' skill level, their interest in teaching, trying or learning new activities, as well as school-related or general needs.

As in previous work, users reported an ideal encounter opportunity when the relational context fits current social context (i.e., a match for 'lifting weights' while in the gym). To detect such 'ideal opportunities', systems need to model which activities are relevant at which places or locations. While age and gender preferences should be taken into account by the system, we learned that in some cases those preferences might be overwritten by particularly opportune fit of relational, social and personal context. To implement this in a system, future work needs to explore the threshold of when opportune context overwrites user preferences.

10.7.2 Towards Passive Context Awareness

The second goal of this study was to explore how we can design user interfaces that inform users about relevant encounter opportunities, and allow them to decide when and how to act on them (RQ2), as well as investigate how contextual preferences and rule sets can be derived from user behavior, user feedback and response delay/timing (RQ3).

User feedback on our ongoing notification stream design highlighted that the notification preview text is important to users to quickly assess if the opportunity is interesting to them. Further, we learned that participants often ignored notifications when they came at inopportune times. Our interview findings show that after a certain time the opportunity becomes irrelevant. This was also highlighted in our field study data analysis showing that participants reacted faster to opportunities they liked, while the response delay was longer for matches they disliked. Based on these findings, we suggest future work to explore different opportunity expiration time frames ranging from 15 minutes to 3 hours.

Moreover, we learned that people would like to be able to set notification timing preferences, e.g., indicate what are good and bad times for meeting people for them, set a maximum amount of wanted notifications per day, and allow them to mute the application for specified time frames. These are novel design ideas that will be explored in future versions of the *Encount'r* application.

Receiving notifications about encounter opportunities while in transit (e.g., driving, commuting by train or bus) turned out to be an important challenge to address. Having crossed paths with an interesting person who is located somewhere between starting point A and end point B (assuming the matched person is not in transit) not only makes it hard for the user to locate the encounter opportunity, but also to organize a meeting. On the other hand, if the matched person is also in transit on the same route, for example, being matched with somebody on the same bus/train, or somebody currently driving on the same / similar route could become interesting to the participant again. Therefore, future application design could explore how commuting / traveling routes could be detected and incorporated into the opportunistic matching. Moreover, our interview findings suggest incorporating repeated 'crossed paths' as well as the current distance to where the opportunity occurred into the application design.

In sum, passive context-awareness is a promising approach for opportunistic social matching. Open challenges however include defining match expiration thresholds, allowing users to provide match timing preferences, as well finding solutions for dealing with opportunities that arise when the user is in transit.

10.7.3 Research Through Design Reflections

Designing an instantiation of an opportunistic social matching system allowed us to think of concrete solutions to the problem space we defined in earlier studies. In this formative evaluation, we assessed *Encount'r* during its early prototype development to provide information about how best to revise and modify for improvement.

We learned that participants found it easy and intuitive to provide reasons for liking or disliking a certain match and already expected the prototype to learn from their input. However, users want to be able to explicitly state certain attributes they never want to be matched on (i.e., blacklist attributes). Therefore, the feedback data collected by *Encount'r* seems a promising approach to build implicit and explicit user preference models.

When we discussed the profile avatar used in *Encount'r* with our participants, we learned that the avatar made the application feel less threatening, but also less real to them. This could be seen as a limitation of our study, as people were not considering the matches to be real. However, we do not have reason to believe that this limitation is very drastic, as interview participants repeatedly referred to matches as real people they were hoping to meet. Delving deeper into the issue, our interviews showed that the avatar moved people's focus away from physical appearance towards profile attributes, as we intended. Also as expected, while people associated picture-based matching with online dating applications like *Tinder*, they acknowledged that *Encount'r* is designed to address a broader spectrum of user goals, such as activity matching, school-related needs, professional networking, and just generally finding new friends. However, people said they would like to have a real picture before meeting someone in-person. One design idea here would be to share a picture only after being reciprocally matched. However, this might result in people simply liking matches to be able to see the picture. Solving this potential issue, *Encount'r* could allow users to share their picture later when they feel ready for it after chatting for a bit. This could still lead to an uncomfortable refection simply based on a shared picture. Some participants agreed that in order to do an activity together (e.g., play soccer), no real picture is required. This brings up the idea of sharing/using a profile picture based on the type of match. Clearly, more research is needed to explore how pictures can be exchanged in a privacy-respecting and socially intelligent way.

We only tested an early prototype of the *Encount'r* application but we received interesting feedback on how a chat feature could enrich the user experience. Our interviews highlight how scheduling support could help users exchange opportune times and places to meet. Based on users' location and match type, the application could suggest a nearby place for a certain activity and a time where both users could meet.

Last, but not least, surprisingly few safety or privacy concerns were brought up. We learned that this was due to the scope of the study being conducted on a university campus with only university students, without real pictures or personal data being exchanged. For future work, we suggest a verification or vetting process and potentially reputation systems to ensure safety and trust. This requires research exploring how reputation and trust could be built into an opportunistic social matching application.

10.8 Limitations

This study was meant as a first prototype evaluation in the field, which is why the sample size was rather small. This resulted in some limitations to this study. The small sample size limited our abilities to generate real matches between participants. Having only hypothetical matches might have influenced the validity of our data. However, the interview findings showed that most of the time participants assumed that the match they were evaluating was real. Another larger field study with real matching between users is planned, but beyond the scope of this work.

Another limitation to the study might be that the application did not allow participants to chat. Participants described that it felt less intimidating to 'like' a match because there was no immediate consequence, i.e., having to chat with the other person. Therefore, our data might be slightly biased towards more 'likes'.

Our sample was gender biased (70.2% male) due to the gender makeup of the campus and *Encount'r* currently being only implemented for Android. In our profiling survey sample out of the 185 Android users, only 17.3% were female, compared to 32.5% female iOS users. In future work, it is important to include iOS users to have a more representative sample.

Finally, as in our previous work, we only had students as subjects, which is why findings might not generalize to other populations.

10.9 Summary

In this chapter, we examined how opportunistic social matching systems could be designed to enable opportunities, instead of just identifying them. We designed, built and evaluated a prototypical opportunistic social matching system (named *Encount'r*) through a field study as well as follow-up interviews. Through this IT artifact, we explored how *passive context-awareness* could be implemented in opportunistic social matching. Moreover, a large-scale user profiling survey (n=401) enabled us to compute baseline rarity measures and successfully operationalize relational context using rarity, passion levels, skills, needs, and offers. Moreover, collected match feedback highlighted how relational context is most predictive of liking a match, while personal context (such as time and location) is most often a reason for disliking a match.

Exploring the concept of passive context-awareness for opportunistic social matching, we learned that our notification design with reason-for-match preview text was very effective at letting users decide at a glance if they wanted to attend or ignore match opportunities. Response times showed that users attended faster (and more often) to opportunities they liked. However, open challenges include defining match expiration thresholds, allowing users to provide match timing preferences, as well finding solutions for dealing with opportunities that arise when the user is in transit. Furthermore, we propose future design iterations for our *Encount'r* app to explore how to build implicit and explicit user preference models from user feedback, as well as to investigate how real profile pictures affect the user experience. In addition, a chat feature to support initial interaction between users would be desirable, as well as perhaps support for scheduling in-person encounters by suggesting nearby places and possible times.

In summary, the contributions of this study include design artifacts and validated mechanisms utilizing contextual data to introduce interesting and relevant people to each other at opportune moments.

CHAPTER 11

CONCLUSION

Opportunistic social matching systems have great potential for mediating chance encounters and supporting the creation of new social ties and social capital. To make them a reality, the aim of this dissertation was to explore how to design such systems that introduce nearby people to each other when the opportunity arises. We proposed a theoretical framework that systematically ordered our knowledge about chance encounter dynamics and categorized determinants into social, personal, and relational factors (Chapter 6). This framework allowed us to develop a research plan to systematically investigate the design of systems that mediate chance encounters and help people to make meaningful new connections. In our first study (Chapter 8), we explored the nature of situations in which opportunities exist for valuable mobile encounters. Insights gained from an interview study suggest that opportune social context relates to sociability of people nearby, familiarity with place and people, perceived safety of the location and jointly attended events and activities. Moreover, opportune personal context is mostly reliant on people's current activity and how busy they are. Finally and most importantly, opportune relational context can be identified based on contextually rare shared and not shared attributes, as well as activity partnering. From these findings we derive novel design concepts to identify valuable mobile encounter opportunities based on social, personal, and relational context, which are instrumental in the implementation of context-aware social matching applications.

As a next step, we conducted a quantitative Experience Sampling Method (ESM) study with a larger sample of random participants to explore how social, personal and relational context could be operationalized to identify valuable mobile encounter opportunities (chapter 8). A generalized linear mixed model analysis showed that *personal context* (mood and busyness) together with the sociability of others nearby are the strongest predictors of people's interest in a social match. Participant interviews further highlighted the role of *relational context* and explained some inconclusive findings. We learned that additional meta-information about user interests is needed to predict matching preference in relation to shared interests (*relational context)*. Based on these findings, we proposed *passion level*, *social network rarity*, and the user's *willingness to teach, learn, or try* an activity to be captured to successfully operationalize *relational context*. Furthermore, we put forward the novel design concept of *passive context-awarenes*s for social matching.

In Chapter 10, we designed, built and evaluated a prototypical opportunistic social matching system (named *Encount'r*) through a field study as well as follow-up interviews. Evaluating how users used our design artifact in the field helped us to discover unanticipated effects and provided a template for bridging the general aspects of the theory to a specific problem space, context of use, and set of target users. A large-scale user profiling survey enabled us to compute baseline rarity measures and successfully operationalize relational context using rarity, passion levels, skills, needs, and offers. Passive context-awareness was shown to be a promising approach for opportunistic social matching. Field study participants valued being informed about contextually relevant match opportunities. The notification text allowed them to glance at the reason for the match and decide to not be interrupted or ignore the encounter opportunity when they were busy. Response times showed that users attended faster (and more often) to opportunities they liked.

This was only the first step in an iterative design process that involves finding and fixing problems to make opportunistic social matching a reality. Future design iterations for our *Encount'r* application could explore how to build implicit and explicit user preference models from user feedback, as well as investigate how real profile pictures affect the user experience. Other open challenges include defining match expiration thresholds, allowing users to provide match timing preferences, as well as finding solutions for dealing with opportunities that arise when the user is in transit. In addition, a chat would be desirable to support initial interaction between users as well as maybe support scheduling of in-person encounters by suggesting nearby places and possible times.

Collectively, this dissertation research extends prior research on social matching by providing an empirical foundation for the design of future mobile systems that are more likely to enable opportunistic social matching. It resulted in validated mechanisms derived from the theoretical model that use contextual data to introduce interesting and relevant people to each other at opportune moments. Moreover, new innovative system affordances for opportunistic social matching systems are outcomes of this research, such as ongoing notification streaming as a form of passive context-awareness and quick and user-friendly feedback screens. This will produce entirely new possibilities for social navigation enabling people to create new, valuable, unexpected relationships on the go.

APPENDIX A

IRB APPROVALS AND CONSENT FORMS

In this appendix you will find the

(1) IRB Approval Form for ESM Study (Dec. 2013)

(2) Consent Form for ESM Study (Dec. 2013)

(3) IRB Renewal for ESM Study (Feb. 2015)

(4) IRB Renewal for Field Study (Sept. 2015)

(5) Renewed Consent Form for Field Study (Sept. 2015)

(1) IRB Approval Form for ESM Study (Dec. 2013)

NJIT
New Jersey's Science & Technology University

Institutional Review Board: HHS FWA 00003246
Notice of Approval
IRB Protocol Number: F 175-13

Principal Investigators: Dr. Quentin Jones
Julia Mayer
Information Systems

Title: Quantitative Study of Match Opportunity Model
Performance Site(s): NJIT:

Type of Review: FULL [x] EXPEDITED [ ]

Type of Approval: NEW [x] RENEWAL [ ] REVISION [ ]

Approval Date: December 1, 2013 Expiration Date: November 30, 2014

1. **ADVERSE EVENTS:** Any adverse event(s) or unexpected event(s) that occur in conjunction with this study must be reported to the IRB Office immediately (973) 596-5825.

2. **RENEWAL:** Approval is valid until the expiration date on the protocol. You are required to apply to the IRB for a renewal prior to your expiration date for as long as the study is active. It is your responsibility to ensure that you submit the renewal in a timely manner.

3. **CONSENT:** All subjects must receive a copy of the consent form as submitted. Copies of signed consent forms must be kept on file with the principal investigator.

4. **SUBJECTS:** Number of subjects approved: 100

5. The investigator(s) did not participate in the review, discussion, or vote of this protocol.

6. **APPROVAL IS GRANTED ON THE CONDITION THAT ANY DEVIATION FROM THE PROTOCOL WILL BE SUBMITTED, IN WRITING, TO THE IRB FOR SEPARATE REVIEW AND APPROVAL.**

(2) Consent Form for ESM Study (Dec. 2013)

NEW JERSEY INSTITUTE OF TECHNOLOGY
323 MARTIN LUTHER KING BLVD.
NEWARK, NJ 07102

CONSENT TO PARTICIPATE IN A RESEARCH STUDY

TITLE OF STUDY:

RESEARCH STUDY:

I,____, have been asked to participate in a research study under the direction of Dr. Quentin Jones, a Professor in the information systems department at NJIT, and Julia Mayer, a PhD student in information systems. Other professional persons who work with them as study staff may assist to act for them.

PURPOSE:

The purpose of this study is to address the issues being faced by current mobile social matching systems which aim to bring people together in the physical world by recommending people nearby. By employing an ESM (Experience Sampling Method), we will have the participants of this study fill out surveys at pre-determined intervals to assess their receptiveness to being introduced to a new person at different times and foreseeably locations throughout their day. Based on our findings we hope to propose new approaches to the identification of opportunities for serendipitous introductions.

DURATION:
My participation in this study will last for 7-10 days.

PROCEDURES:
I have been told that, during the course of this study, the following will occur:

1) I will fill out a short profile survey to collect demographic and user profile data such as interests, educational and professional background information.

2) I will download an ESM app to my smartphone which will send me notifications to fill out a short surveys.

3) I will be asked to answer a short survey on my phone at the given date/time a notification is activated. Questions will revolve around understanding my motivations and preferences with respect to meeting other people in my current situation.

4) I must not reveal any criminal or illegal information during the study and am not protected by privilege.

NJIT New Jersey's Science & Technology University

Approved by the NJIT IRB on 12/1/2013 F175-13
Modifications may not be made to this consent form without NJIT IRB approval

PARTICIPANTS:
I will be one of about 100 participants in this study.

EXCLUSIONS:
I will inform the researcher if any of the following apply to me:

1) I do not have a compatible smart phone(IPhone/Android)
2) I do not have a data plan on my smart phone.

RISKS/DISCOMFORTS:

I have been told that the study described involves no known risk and/or discomforts. There may be risks and discomforts that are not yet known. I fully recognize that there are risks that I may be exposed to by volunteering in this study which are inherent in participating in any study; I understand that I am not covered by NJIT's insurance policy for any injury or loss I might sustain in the course of participating in the study.

CONFIDENTIALITY:
I understand confidential is not the same as anonymous. Confidential means that my name will not be disclosed if there exists a documented linkage between my identity and my responses as recorded in the research records. Every effort will be made to maintain the confidentiality of my study records. If the findings from the study are published, I will not be identified by name. My identity will remain confidential unless disclosure is required by law.

PAYMENT FOR PARTICIPATION:
I have been told that I will receive $0.00 compensation for my participation in this study.

RIGHT TO REFUSE OR WITHDRAW:
I understand that my participation is voluntary and I may refuse to participate, or may discontinue my participation at any time with no adverse consequence. I also understand that the investigator has the right to withdraw me from the study at any time.

INDIVIDUAL TO CONTACT:
If I have any questions about my treatment or research procedures, I understand that I should contact the principal investigator at:

Dr. Quentin Jones
Department of Information Systems, NJIT
University Heights, Newark NJ 07102
Office: 5600 GITC
732-221-6502
qjones@njit.edu

Julia Mayer
Department of Information Systems, NJIT
University Heights, Newark NJ 07102
Office: 5600 GITC
757-585-4219

(3) IRB Renewal for ESM Study (Feb. 2015)

NJIT

New Jersey's Science & Technology University

Institutional Review Board: HHS FWA 00003246
Notice of Approval
IRB Protocol Number: F175-13

Principal Investigators: Quentin Jones
Julia Mayer
Information Systems

Title: Quantitative Study of Match Opportunity Model

Performance Site(s):

Type of Review: FULL [X] EXPEDITED [ ]

Type of Approval: NEW [ ] RENEWAL [X] REVISION [X]

Approval Date: December 1, 2013, February 23, 2015 Expiration Date: November 30, 2015

1. **ADVERSE EVENTS:** Any adverse event(s) or unexpected event(s) that occur in conjunction with this study must be reported to the IRB Office immediately (973) 596-6053.

2. **RENEWAL:** Approval is valid until the expiration date on the protocol. You are required to apply to the IRB for a renewal prior to your expiration date for as long as the study is active. It is your responsibility to ensure that you submit the renewal in a timely manner.

3. **CONSENT:** All subjects must receive a copy of the consent form as submitted. Copies of signed consent forms must be kept on file with the principal investigator. The following items were added:
   - Duration of study 5 days
   - Collected information will only be reviewed by the researches conducting the study and no third party entity will have access
   - Financial compensation up to $25 ($5 base for signing up and $1 per survey filled out – maximum 20 surveys fill –out)

4. **SUBJECTS:** Number of subjects approved:

5. The investigator(s) did not participate in the review, discussion, or vote of this protocol.

6. **APPROVAL IS GRANTED ON THE CONDITION THAT ANY DEVIATION FROM THE PROTOCOL WILL BE SUBMITTED, IN WRITING, TO THE IRB FOR SEPARATE REVIEW AND APPROVAL.**

Norma Rubio, IRB Chair,

Norma I Rubio

(4) IRB Renewal for Field Study (Sept. 2015)

NJIT New Jersey's Science & Technology University

Institutional Review Board: HHS FWA 00003246
Notice of Approval
IRB Protocol Number: F175-13

Principal Investigators: **Julia Mayer, PhD Candidate (IS)**
Quentin Jones (IS)

Title: **Quantitative Study of Match Opportunity Model**

Type of Review: FULL [X] EXPEDITED [ ]

Type of Approval: NEW [ ] RENEWAL [X] REVISION [ ]

Approval Date: **March 16, 2014, September 17, 2015** Expiration Date: **September 17, 2016**

1. **ADVERSE EVENTS:** Any adverse event(s) or unexpected event(s) that occur in conjunction with this study must be reported to the IRB Office immediately (973) 596-6053.

2. **RENEWAL:** Approval is valid until the expiration date on the protocol. You are required to apply to the IRB for a renewal prior to your expiration date for as long as the study is active. It is your responsibility to ensure that you submit the renewal in a timely manner. Minor changes – data collection session will be repeated at 3-4 months intervals over a course of two years. Minor changes are: 1) extended profile survey; 2) ESM survey redesign; 3) and updated consent form.

3. **CONSENT:** All subjects must receive a copy of the consent form as submitted. Copies of signed consent forms must be kept on file with the principal investigator.

4. **SUBJECTS:** Number of subjects approved: **50**

5. The investigator(s) did not participate in the review, discussion, or vote of this protocol.

6. **APPROVAL IS GRANTED ON THE CONDITION THAT ANY DEVIATION FROM THE PROTOCOL WILL BE SUBMITTED, IN WRITING, TO THE IRB FOR SEPARATE REVIEW AND APPROVAL.**

Norma Rubio, IRB Co -Chair,

Norma I Rubio

(5) Renewed Consent Form for Field Study (Sept. 2015)

NEW JERSEY INSTITUTE OF TECHNOLOGY
323 MARTIN LUTHER KING BLVD.
NEWARK, NJ 07102

CONSENT TO PARTICIPATE IN A RESEARCH STUDY

TITLE OF STUDY: Quantitative Study of Match Opportunity Model

RESEARCH STUDY:

I, ____, have been asked to participate in a research study under the direction of Dr. Quentin Jones, a Professor in the information systems department at NJIT, and Julia Mayer, a PhD student in information systems. Other professional persons who work with them as study staff may assist to act for them.

PURPOSE:
The purpose of this study is to address the issues being faced by current mobile social matching systems which aim to bring people together in the physical world by recommending people nearby. By employing an ESM (Experience Sampling Method), we will have the participants of this study fill out surveys at pre-determined intervals to assess their receptiveness to being introduced to a new person at different times and foreseeably locations throughout their day. Based on our findings we hope to propose new approaches to the identification of opportunities for serendipitous introductions.

DURATION:
My participation in this study will last for 5 days.

PROCEDURES:
I have been told that, during the course of this study, the following will occur:

1) I will download a mobile app to my smartphone

2) I will fill out an extensive user profile survey (via *TellUsWho* tool) to collect demographic and user profile data such as interests, educational and geographical background information.

3) I will be notified by the app to provide feedback on hypothetical match recommendations on my phone. Feedback-questions will revolve around understanding my motivations and preferences with respect to meeting other people in my current situation. The collected information will be only reviewed by the researchers conducting the study and that no third party entity will have access.

4) I must not reveal any criminal or illegal information during the study and am not protected by privilege.

PARTICIPANTS:
I will be one of about 50 participants in this study.

EXCLUSIONS:
I will inform the researcher if any of the following apply to me:

1) I do not have a compatible Android smartphone
2) I do not have a data plan on my smart phone.

NJIT New Jersey Institute of Technology Approved NJIT IRB 9/18/2015 F175-13

RISKS/DISCOMFORTS:
I have been told that the study described involves no known risk and/or discomforts. There may be minimal risks and discomforts that are unexpected. I fully recognize that there are risks that I may be exposed to by volunteering in this study which are inherent in participating in any study including unauthorized third party access/hacking of mobile; I understand that I am not covered by NJIT's insurance policy for any injury or loss I might sustain in the course of participating in the study.

CONFIDENTIALITY:
I understand confidential is not the same as anonymous. Confidential means that my name will not be disclosed if there exists a documented linkage between my identity and my responses as recorded in the research records. Every effort will be made to maintain the confidentiality of my study records. If the findings from the study are published, I will not be identified by name. My identity will remain confidential unless disclosure is required by law.

PAYMENT FOR PARTICIPATION:
I have been told that I will receive $25.00 compensation for my participation in this study.

RIGHT TO REFUSE OR WITHDRAW:
I understand that my participation is voluntary and I may refuse to participate, or may discontinue my participation at any time with no adverse consequence. I also understand that the investigator has the right to withdraw me from the study at any time.

INDIVIDUAL TO CONTACT:
If I have any questions about my treatment or research procedures, I understand that I should contact the principal investigator at:

Dr. Quentin Jones
Department of Information Systems, NJIT
University Heights, Newark NJ 07102
Office: 5600 GITC
732-221-6502
qjones@njit.edu

Julia Mayer
Department of Information Systems
University Heights, Newark NJ 07102
Office: 4215 GITC
757-585-4219
jam45@njit.edu

If I have any addition questions about my rights as a research subject, I may contact:

Farzan Nadim, IRB Chair
New Jersey Institute of Technology
323 Martin Luther King Boulevard
Newark, NJ 07102
(973) 596-8453
farzan@njit.edu / irb@njit.edu

SIGNATURE OF PARTICIPANT
I have read this entire form, or it has been read to me, and I understand it completely. All of my questions regarding this form or this study have been answered to my complete satisfaction. I agree to participate in this research study.

Participant Name ______________________________

____

Signature ______________________________

Date ______________________________

NJIT New Jersey Institute of Technology Approved NJIT IRB 9/18/2015 F175-13

APPENDIX B

MOBILE SOCIAL MATCHING SURVEY

This is the mobile social matching survey, which was computerized and distributed via email.

Mobile Social Recommendation Survey

This survey aims at better understanding user needs for the design of a mobile social recommendation application. Mobile social recommendation (or matching) applications recommend people to other people based on a variety of reasons. Reasons could be shared interests, striking up a good conversation, or the need for professional knowledge or specific expertise to solve a problem.

Before starting the survey please consider the following possible scenario in order to better understand the survey questions:

Sara is an NJIT undergrad student. She grew up in **Texas** and went to **Lufkin High School** there. Her parents are **Italian** so she speaks a little bit of Italian. During the weekend she enjoys watching a movie or reading a thriller. She likes outdoor stuff and picnics.

She is using a *mobile social recommendation application* on her smartphone which sends her *privacy-respecting notifications* about people nearby she could be interested in getting to know.

One day she gets a notification on her phone telling her that there is **somebody nearby from Texas who went to the same high school as her.** This person also **speaks Italian** and they have a **mutual friend.**

Since she doesn't know anybody at NJIT who is from Texas and speaks Italian, she gets curious and decides to *get introduced* to this person through the mobile app.

Please read the questions carefully and provide answers based on your own interest in the different situations.

The information that you give in the study will be handled confidentially. Your name will not be used in any report.

1. Interests

List three of your interests

e.g., hobbies (stamp collecting, baseball, etc.) or things you are fan of, you like to watch/listen (a specific sports team, TV show, band, music style, etc.)

1.

2.

3.

How common* is someone with this interest...	a)...in your (main) social circle?	b)...nearby when you go out socially?	c)...at your work/school?	d)...in the area you currently live?
Interest 1	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Interest 2	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Interest 3	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Interest 1 + 2 + 3	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common

**Your best guess / your own assessment*

Would you be interested in one of the following, if there was somebody with the same interest(s)...?	On your computer	On your phone		
	This person lives/works in your geographical area or regularly visits it.	This person is currently nearby while you are at an event, place or activity related to this interest (e.g., concert, sports game, convention, etc.)	This person is currently nearby while you are walking around NJIT campus	This person is currently nearby while you are in Japan** (e.g. for a business trip, exchange semester, etc)
Interest 1	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Interest 2	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Interest 3	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Interest 1 + 2 + 3	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	N/A *(since you can't be at 3 places/events at the same time)*	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)

***If you happen to be Japanese, assume you are in Italy.*

2. Needs

List something you need a partner for (e.g. jogging, dancing)

1.

List something you need help for (e.g., math tutoring, car repairing)

2.

List something you could offer to someone (service, help, knowledge, e.g. guitar lessons)

3.

How common* is...	a)...in your (main) social circle?	b)...nearby when you go out socially?	c)...at your work/school?	d)...in the area you currently live?
...the need of a partner for *Need 1*	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	extremly rare, 2, 3, 4, 5, 6, 7 very common
...someone who offers *Need 2*	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common
...someone who needs *Need 3*	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common

**Your best guess / your own assessment*

Would you be interested in one of the following, if there was somebody ... ?	On your computer	On your phone		
	This person lives/works in your geographical area or regularly visits it.	**This person is currently nearby while you are at an event, place or activity related to this need/offer** (e.g., dancing club, auto shop, etc.)	**This person is currently nearby while you are walking around NJIT campus**	**This person is currently nearby while you are in Japan****(e.g. for a business trip, exchange semester, etc)
...who also needs a partner for *Need 1*	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)
...who offers *Need 2*	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)
...who needs *Need 3*	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)

***If you happen to be Japanese, assume you are in Italy.*

3. Geographical Background

List important points about your geographical background
e.g., home country, nationality, origin, home state, home town, native language, other spoken language, other cities/countries you lived in, etc.

1.

2.

3.

How common* is it to have this geographic background...	a)...in your (main) social circle?	b)...nearby when you go out socially?	c)...at your work/school?	d)...in the area you currently live?
Geo Background 1	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	extremly rare, 2, 3, 4, 5, 6, 7 very common
Geo Background 2	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common
Geo Background 3	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common
Geo Background 1 + 2 + 3	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common	1 extremly rare, 2, 3, 4, 5, 6, 7 very common

*Your best guess / your own assessment

Would you be interested in one of the following, if there was somebody who also has this geographic background...?	On your computer	On your phone		
	This person lives/works in **your geographical area** or regularly visits it.	This person is currently **nearby while you are at an event, place or activity related to this background** (e.g., national celebration, in your hometown, etc.)	This person is currently **nearby while you are walking around NJIT campus**	This person is currently **nearby while you are in Japan**** (e.g. for a business trip, exchange semester, etc)
Geo Background 1	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Geo Background 2	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Geo Background 3	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Geo Background 1 + 2 + 3	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	N/A *(since you can't be at 3 places/events at the same time)*	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)

***If you happen to be Japanese, assume you are in Italy.*

4. Educational Background

List important points about your educational background
e.g., name of previous high school/college, major/degree, research interest, etc.

1.

2.

3.

How common* is it to have this educational background...	a)...in your (main) social circle?	b)...nearby when you go out socially?	c)...at your work/school?	d)...in the area you currently live?
Edu Background 1	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	extremly rare 2 3 4 5 6 7 very common
Edu Background 2	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common
Edu Background 3	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common
Edu Background 1 + 2 + 3	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common

*Your best guess / your own assessment

Would you be interested in one of the following, if there was somebody with the same educational background...?	On your computer	On your phone		
	This person lives/works in **your geographical area** or regularly visits it.	This person is currently **nearby while you are at an event, place or activity related to this background** (e.g., at your previous high school, research interest-related conference, etc.)	This person is currently **nearby while you are walking around NJIT campus**	This person is currently **nearby while you are in Japan**** (e.g. for a business trip, exchange semester, etc)
Edu Background 1	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Edu Background 2	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Edu Background 3	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Edu Background 1 + 2 + 3	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	N/A *(since you can't be at 3 places/events at the same time)*	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)

***If you happen to be Japanese, assume you are in Italy.*

5. Distinct Characteristics

List three things which you consider important or distinct about you
e.g., religious, athletic, speaking French, lived in Italy, dragon tattoo, etc.

1.

2.

3.

How common* is this ...	a)...in your (main) social circle?	b)...nearby when you go out socially?	c)...at your work/school?	d)...in the area you currently live?
Characteristic 1	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	extremly rare 2 3 4 5 6 7 very common
Characteristic 2	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common
Characteristic 3	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common
Characteristic 1 + 2 + 3	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common	1 extremly rare 2 3 4 5 6 7 very common

*Your best guess / your own assessment

Would you be interested in one of the following, if there was somebody with the same thing(s) listed in his/her profile...?	On your computer	On your phone		
	This person lives/works in **your geographical area** or regularly visits it.	This person is currently **nearby while you are at an event, place or activity related to this distinct characteristic** (e.g., church, language school, tattoo convention, etc.)	This person is currently **nearby while you are walking around NJIT campus**	This person is currently **nearby while you are in Japan**** (e.g. for a business trip, exchange semester, etc)
Characteristic 1	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Characteristic 2	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Characteristic 3	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	○ not interested (N/A) ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)
Characteristic 1 + 2 + 3	○ not interested ○ notification on my PC ○ notification + get introduced (chat / profile exchange)	N/A *(since you can't be at 3 places/events at the same time)*	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)	○ not interested ○ notification on my phone ○ notification + get introduced (chat / profile exchange)

***If you happen to be Japanese, assume you are in Italy.*

6. Places

List three places you regularly go to / hang out at
e.g., campus center, gym, mall, library, highlander pub, central park, laurel hall, etc.

1.

2.

3.

How common* is it to regularly go to...	a)...in your (main) social circle?	b)...nearby when you go out socially?	c)...at your work/school?	d)...in the area you currently live?
Place 1	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Place 2	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Place 3	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Places 1 + 2 + 3	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common

*Your best guess / your own assessment

Would you be interested in one of the following, if there was somebody who regularly also goes to...?	On your computer	On your phone		
	This person lives/works in **your geographical area** or regularly visits it.	This person is currently **nearby while you are at at THIS place**	This person is currently **nearby while you are walking around NJIT campus**	This person is currently **nearby while you are in Japan**** (e.g. for a business trip, exchange semester, etc)
Place 1	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)
Place 2	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)
Place 3	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)
Places 1 + 2 + 3	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	N/A *(since you can't be at 3 places/events at the same time)*	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)

***If you happen to be Japanese, assume you are in Italy.*

7. Friends

List the names of your three closest friends
(first names, nicknames are ok)

1.

2.

3.

How common* are friends of...	a)...in your (main) social circle?	b)...nearby when you go out socially?	c)...at your work/school?	d)...in the area you currently live?
Friend 1	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Friend 2	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Friend 3	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common
Friends 1 + 2 + 3	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common	○ 1 extremly rare ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 very common

**Your best guess / your own assessment*

Would you be interested in one of the following, if there was somebody who also is close friends with...?	On your computer	On your phone		
	This person lives/works in your geographical area or regularly visits it.	This person is currently nearby while you are at an event, place or activity WITH THIS friend	This person is currently nearby while you are walking around NJIT campus	This person is currently nearby while you are in Japan** (e.g. for a business trip, exchange semester, etc)
Friend 1	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)
Friend 2	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)
Friend 3	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	◯ not interested (N/A) ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)
Friends 1 + 2 + 3	◯ not interested ◯ notification on my PC ◯ notification + get introduced (chat / profile exchange)	N/A *(since you can't be at 3 places/events at the same time)*	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)	◯ not interested ◯ notification on my phone ◯ notification + get introduced (chat / profile exchange)

***If you happen to be Japanese, assume you are in Italy.*

Overall Rating

In general, how interesting was each of the previous sections to you, in terms of getting to know people based on these user attributes?

1. *Interests*	○ 1 not at all interesting	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7 extremely interesting
2. *Needs*	○ 1 not at all interesting	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7 extremely interesting
3. *Geographical Background*	○ 1 not at all interesting	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7 extremely interesting
4. *Educational Background*	○ 1 not at all interesting	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7 extremely interesting
5. *Distinct Characteristics*	○ 1 not at all interesting	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7 extremely interesting
6. *Places*	○ 1 not at all interesting	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7 extremely interesting
7. *Friends*	○ 1 not at all interesting	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7 extremely interesting

THANK YOU FOR TAKING THIS SUREVY.

If you have any questions, please contact Julia Mayer (jam45@njit.edu).

APPENDIX C

PROFILING SURVEY

Below you can find the social matching profile survey that was used in Study 3. It was computerized and distributed via email.

Social Matching Profiling Survey

1. **Name:** ____
First   Last

2. **Email** ____________________@njit.edu

3. **What kind of cell phone do you use as your personal device?**

□ Android   □ iPhone   □ Other:________________

4. **What gender do you identify with?**

□ Female   □ Male   □ Rather not say

5. **Select the one that best describes you today:**

□ Single   □ in a relationship   □ Married   □ Rather not say

6. **In which year were you born:** _______________________________________

7. **Where did you grow up?** __________________________________
City, State / Country

8. **Nationality:** _______________________________________

9. **Where do you currently live?** _______________________________
City, State / Country

10. **What is your native language / mother tongue?** __________________________

11. **Please list any other languages that you speak:** _____________________________

12. **Student Type:**   □ Undergraduate   □ Graduate

13. **Status:**   □ Part Time   □ Full Time

14. **Commuter:**   □ Live on Campus   □ Commuter

15. **What's your current Major?** ____________________________________

School & Work
Please first, complete the questions in the left column, and then answer the question in the right column in regards to items in the left column.

15. I'm involved in the following campus organizations: (e.g. Clubs, Athletic, Sorority)	16. How passionate are you about this?						
a)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
b)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
c)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
17. I'm currently working in the field of:	18. How passionate are you about this?						
	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
19. I'm currently volunteering in the field of:	20. How passionate are you about this?						
	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
21. When meeting with classmates on campus, we usually do…. (List in rows below)	22. How passionate are you about this?						
a)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
b)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
c)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
23. I'm looking for someone to study for….(List in rows below)	24. How passionate are you about this?						
a)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
b)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
c)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate

Interest & Hobbies
Please first, complete the questions in the left column, and then answer the question in the right column in regards to items in the left column.

25. My favorite sports/TV series/movies to watch are... (List in rows below)	26. How passionate are you about this?						
a)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate
b)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate
c)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate

27. My favorite sports / activities to do are…	28. How passionate are you about this?						
a)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate
b)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate
c)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate

29. My favorite games are…	30. How passionate are you about this?						
a)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate
b)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate
c)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate

31. Other favorite things I like are …	32. How passionate are you about this?						
a)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate
b)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate
c)	Not really passionate	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	Extremely passionate

33. Some things that I like, but none of my friends like are…	34. How passionate are you about this?
a)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
b)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
c)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
35. I always wanted to try …	36. How passionate are you about this?
a)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
b)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
c)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
37. I'm looking for people for to do / talk about…	38. How passionate are you about this?
a)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
b)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
c)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
39. I need some help with…	40. How passionate are you about this?
a)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
b)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate
c)	Not really passionate □ 1 □ 2 □ 3 □ 4 □ 5 Extremely passionate

41. I would like to learn / get better at...	42. How passionate are you about this?						
a)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
b)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
c)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate

43. I'm really good at...	44. How passionate are you about this?						
a)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
b)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
c)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate

45. I just started learning / doing…	46. How passionate are you about this?						
a)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
b)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
c)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate

47. Things I'm willing to teach / help out others with are…	48. How passionate are you about this?						
a)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
b)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate
c)	Not really passionate	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely passionate

Please rate the following statements on how characteristic they are for you:

I like to be with people.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I welcome the opportunity to mix socially with people.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I prefer working with others rather than alone.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I find people more stimulating than anything else.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I'd be unhappy if I were prevented from making many social contacts.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I am socially somewhat awkward.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I don't find it hard to talk to strangers	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I feel tense when I'm with people I don't know well.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
When conversing I worry about saying something dumb.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I feel nervous when speaking to someone in authority.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I am often uncomfortable at parties and other social functions.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic
I am more shy with members of the opposite sex.	Extremely uncharacteristic	□ 1	□ 2	□ 3	□ 4	□ 5	Extremely characteristic

Thank you for filling out this survey!

We will contact you within 14 days if you qualify to participate in the mobile app study ($20 compensation).

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