Supporting Opportunities for Context-Aware Social Matching: An Experience Sampling Study

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ABSTRACT

Mobile social matching systems aim to bring people together in the physical world by recommending people nearby to each other. Going beyond simple similarity and proximity matching mechanisms, we explore a proposed framework of relational, social and personal context as predictors of match opportunities to map out the design space of *opportunistic social matching systems*. We contribute insights gained from a study combining Experience Sampling Method (ESM) with 85 students of a U.S. university and interviews with 15 of these participants. A generalized linear mixed model analysis (n=1704) showed that personal context (mood and busyness) as well as sociability of others nearby are the strongest predictors of contextual match interest. Participant interviews suggest operationalizing relational context using *social network rarity* and *discoverable rarity*, and incorporating *skill level* and *learning/teaching needs* for activity partnering. Based on these findings we propose passive context-awareness for opportunistic social matching.

Author Keywords

Opportunistic Social Matching; Context-Aware Computing; Social Recommender Systems; Experience Sampling

ACM Classification Keywords

H.1.2 [Information Systems]: User/Machine Systems.

INTRODUCTION

While we often are surrounded by interesting people, it is problematic to identify who they are and how to connect with them. Social barriers often prevent social encounters in environments where people do not know each other and we regularly have to rely on serendipity to meet or to be introduced to new friends and acquaintances around us. However, the number and strength of social network ties is important for people's mental health [33] and is also related to academic success with a significant relationship existing between first year university dropout rates and social connectivity [39]. Mobile social matching systems recommend people to other nearby people of potential interest via mobile devices [36]. In theory, such systems decrease social barriers for initiating face-to-face interaction with an unfamiliar person, support the creation of new social ties, and increase social capital. Unfortunately, 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 [32,38]. A key challenge that we explore here is to 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. The social matching systems that have become successful so far are mostly mobile online dating applications, such as *Tinder, Grindr, or Happn.* Another type of matching tool is based on service offers and service needs, such as ride sharing apps *Uber and Lyft* that match drivers with users needing a ride. Less successful mobile social applications aim to connect users with new people for reasons other than dating. Mobile professional networking apps, like *Weave* and *Caliber*, promise to introduce users to entrepreneurs, investors, and other people who could unlock career opportunities. *Highlight* 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. 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 [21]. 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 [14,28]. 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 [5,12,35]. Moreover, users are matched for a single specific purpose, e.g., "Connect me with nearby female singles" (*Tinder*), or "Connect me with nearby available drivers" (*Uber*). 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 social activities.

In this paper we explore the design of *opportunistic social matching systems* that introduce people proactively without a specific user query or explicit user goal, but instead when the opportunity arises. We base our research on prior work, which proposes *relational, social and personal context* be used as predictors of match opportunities [23,25]. Opportunities for chance encounters arise when two (or more) people are currently interesting to each other, e.g., have a shared attribute (*opportune relational context*), and are currently willing/able to meet someone new based on their internal state of mind (*opportune personal context*) and external social factors (*opportune social context)*.

This paper is one of the first attempts to build upon this framework and explore how to operationalize relational, personal, and social context to predict people's in-situ match interest using a combination of Experience Sampling Method (ESM) [20] and semi-structured interviews. In an ESM study, subjects carry some form of mobile device that randomly signals participants to fill out a survey throughout the day. This allows for 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 operationalizing concepts of relational, personal, and social context and deriving more concrete design implications for opportunistic social matching applications.

We start by discussing relevant background literature and then present our research question and associated hypotheses. A description of the research methods is followed by our results and discussion of our findings.

BACKGROUND

This section briefly summarizes the literature on previous mobile social matching systems and social tie formation, as well as context-aware computing.

Social Matching

The most common cliché about human nature is that *birds of a feather flock together* (similarity-attraction effect) [27]. Homophily, "the love of the same", is the tendency of people to bond with others who are similar to them. Moreover, people tend to develop a preference for people (or things) that are physically close and seen regularly, hence more familiar to them *(Mere Exposure Theory* [40]). Therefore, early research on mobile social matching was aimed at building prototypes with a focus on proximity and similarity. *Nokia Sensor* [31] relied on Bluetooth beacons to discover nearby people and to communicate with them. *Social Net* [35] used explicit social network information and RF-based devices to introduce people located in proximity of each other using a common friend. *Social Serendipity* [12] used Bluetooth and a database of user profiles to recommend face-to-face interactions between nearby users who share common preferences. *WhozThat?* [5] shared social networking IDs locally to help facilitate users finding others with common interests.

While similarity and proximity definitely play a significant role in social tie formation [6,9,13,30], 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 [2]. For example, people often interact with similar others because they have more opportunities to meet similar others than to meet those that are dissimilar [15,19,22]. Opportunities are shaped and constrained by various institutionally organized arrangements, such as work, school, family, or neighborhoods. Along the same lines, literature consistently 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) [14,28].

Context-Aware Computing

Mobile phones potentially have access to vast amounts of contextual information that current social matching systems do not leverage. *Context-aware computing* is a computing paradigm that aims at understanding the user's current context with the goal of adjusting system behavior to the situation in which the user is immersed [1,10,11].

Context in the computing field has been defined as "*location, identities of nearby people and objects, and changes to those objects"* [34] and further specified 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"* [1]. 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 [11] argues that context should be understood as a *relational property* between objects or activities defining whether something is contextually relevant to some particular activity. Mayer et al. [23,25,26] proposed making social matching *context-aware* (i.e., opportunistic) by considering *relational, personal* and *social context* to identify social encounter opportunities. *Relational context* includes factors defining the relationship between people, e.g., shared attribute type (demographic, interest, need) or shared attribute rarity. Opportune *personal context* was found to be mostly reliant on people's current activity, mood/openness to meet someone in general, and how busy they are, while opportune *social context* is reliant on external social settings, e.g., current place, people nearby, and organized events and activities.

While physical locations, like GPS coordinates, do not have any substantial meaning, *place* refers to how people come to understand certain locales [17,18,37]. A place is "a space, which is *invested with understandings* of behavioral appropriateness, cultural expectations" [16].

Moreover, prior work differentiates between different levels of interactivity for context-aware applications [3,7]. *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, where *active context-awareness* autonomously changes the application behavior according to the sensed information.

Based on this review of prior work, our goal 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:

H_1: People's interest in meeting a recommended person (match interest) is related to relational context (shared attribute type and contextual rarity).

H_2: Match interest is related to personal context (mood and busyness).

H_3: 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).

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

Figure 1 shows the analysis model, which was used to guide the collection of empirical data to test our hypotheses.

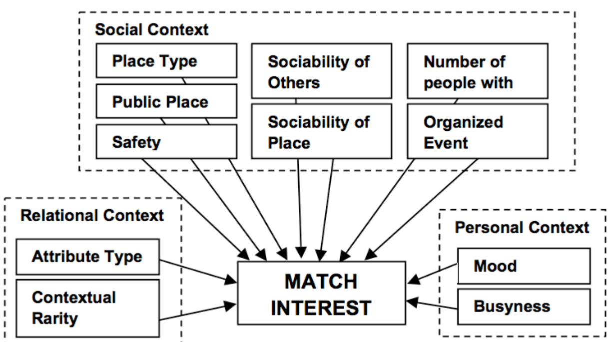


Figure 1. Overview of Analysis Model

METHOD

In order to examine our hypotheses, we conducted a study combining Experience Sampling Method (ESM) [8,20] with participant interviews. ESM participants were probed several times daily on their mobile devices, and at each time they completed a short survey. This procedure allowed us to collect large-scale quantitative data about users' momentary match preferences in a variety of contexts. Furthermore, using ESM entries as a memory aid in interviews enabled us to collect in-depth insights into real situations and experiences that would have been hard to gather otherwise. In addition, the interviews allowed us to assess construct validity of our survey instrument to better understand quantitative results.

Experience Sampling Method Questionnaire

The development of an Android and an iPhone ESM application allowed us to recruit a representative sample. Recruited participants installed the ESM application on their smartphone and then received notifications five times per day at random times (between 7am and 10pm). For each signal/probe they were asked if they were interested in meeting another college student (*match interest)* with whom they had something in common (*relational context)*, and then filled out a series of questions about their current situation (*personal and social context*) (Table 1).

In order to operationalize *relational context* we asked participants to fill out a short pre-study profile survey including three demographics (nationality, hometown and current city), five interests, and three needs (e.g., an activity they need a partner for). The ESM algorithm then cycled through these user profile attributes to be included in [Q1] and [Q2]. This way we collected *match interest* for different *attribute types* (demographic, interest, need) and *contextual attribute rarity* measures [Q1] in each sampled context.

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]

Table 1. ESM Survey Construct Measures

We also asked participants in the pre-study survey to enter five places they go to in a typical week to allow them to quickly select their current place from a prepopulated list [Q5]. 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.

Participant Interviews

We conducted interviews with a subset of our ESM participants. For each interview participant, we printed all ESM responses as a memory aid for discussing specific experiences. We delved deeper into how the different shared attributes included in [Q1] (*relational context)* influenced participants' *match interest*. Furthermore, we discussed how *match interest* varied in different situations captured by the ESM (*personal and social context*).

Data Collection and Analysis Procedures

After several rounds of pilots, 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 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 [14]). Furthermore, students live particularly nomad lifestyles [4], monitor their smartphones constantly, and have set schedules [29], leading to them needing to plan social life within their already tight schedule.

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 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 (*my bedroom*), or referred to activities (*driving*, *doing laundry*). As discussed earlier, there are several challenges revolving around the *notion of place* in social computing systems [16–18]. In order to analyze *place* entries on a high-level, we broke them down into categories: *Homes, Educational, Social, In Transit, Business, Work, Sports,* and *Other*.

After an initial data analysis from the first 50 ESM participants, we invited subsequent participants who had completed surveys at least at three different places, and were available within three days after completing the ESM study (for better recall) for an optional follow-up interview, compensated with $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.

ESM RESULTS

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.

Descriptive Statistics

Overall, participants were interested in meeting the recommended person (i.e., responded 'yes' to [Q1]) 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 meet people, saying 'Yes' or 'Yes but not now' roughly 75% of the times.

Table 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 rarer (mean=3.48) than when they were interested (mean=3.90). This is contrary to our expectations and prior work [23,25,26]. 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. *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 *safety* can be seen across different levels of interest, but when responding with 'yes but not now' the current place was rated the least safe.

	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 2. Mean Values of Context Variables per Match Interest

	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**

Table 3. Match Interest per Categorical Context Variables

Table 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.

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.

H_1: 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% 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 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 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.

	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 - n.s.)	*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".

Table 4. Fixed Effect Coefficients of the Generalized Linear Mixed Model for Predicting Match Interest

H_3: Match interest is related to social context

Significant differences in match interest were found for being at an *organized event:* Pearson $\chi^2(4, n=1841)=10.117$, $p=0.038$, and being at a *public vs. private place*: $\chi^2(4, n=1841)=13.355$, $p=0.010$. Furthermore, we found significant differences in match interest for the different *place types*: $\chi^2(14, n=1741)=25.171$, $p=0.033$. 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 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%.

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.

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.

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).

Shared Rare Attributes

Supporting previous work [23,25,26], 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 rare 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/interest in question. A quote from Leon from Brazil, who was in the U.S. 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.

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.

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.

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.

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.*"

On the other hand, as anticipated, reasons for 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 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.

Social Context

Social context is the social situation the participants found themselves in at the time of the inquiry. The mixed model analysis showed *sociability of others* as the only part of *social context* significantly predicting 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 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 meet other college students.

Number of People Participant Was With

On the one hand, participants mentioned wanting to meet someone when they were alone (similarly to previous work [23,25]): "*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)

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."*

Sociability of People and Place

We inferred from the ESM results that the more social the environment, the more interested people are in meeting someone new. However, similar to above inconclusive results from the *number of people with*, we 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.

Compatibility of Relational, Personal and Social Context

It was the "right" combination of the situation and person that led 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 had 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: "*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."*

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.

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.

DESIGN IMPLICATIONS AND FUTURE RESEARCH

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

Operationalizing Relational, Social, and Personal Context

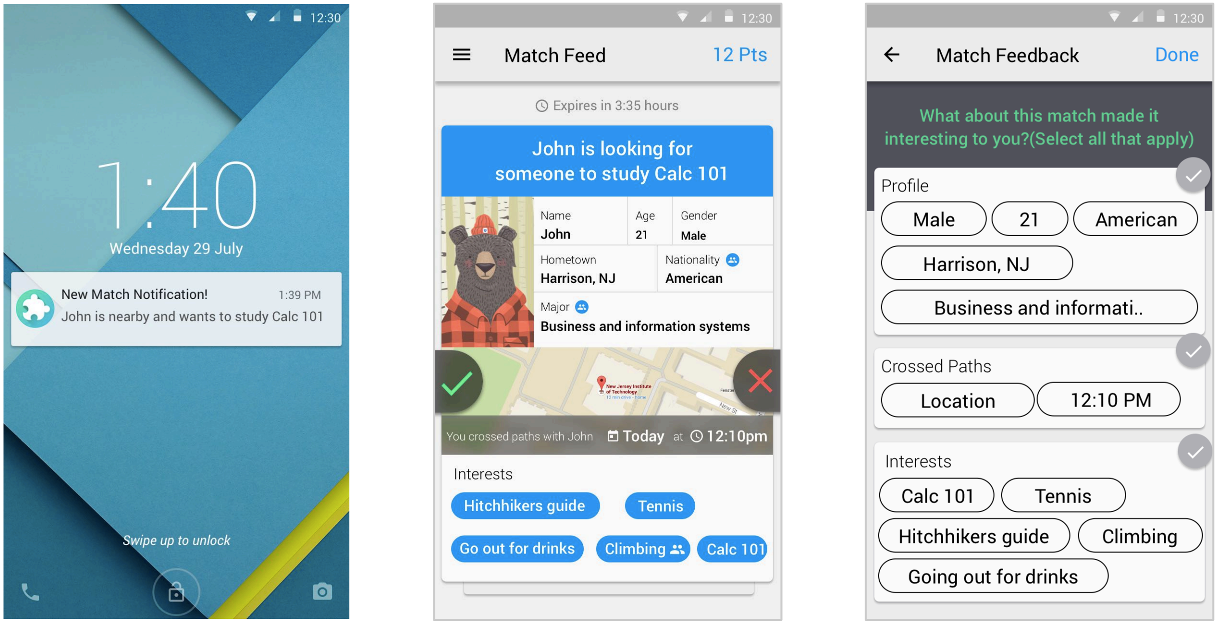
While prior work repeatedly suggested that *relational context*, and in particular the rarity of the shared attribute, influences the match decision, in our data analysis neither *contextual rarity* nor *attribute type* were a significant predictor of match interest. However, we found that some of our 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, interviewees conceptualized *rarity* in a different way than we did in our ESM survey, where respondents had to 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, (2) would require user input.

We further learned that general interests are insufficient to operationalize *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). Therefore, 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 [23,25], 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 lifting buddy while at the gym).



(a) Ongoing Notification of Nearby Encounter Opportunities

(b) Match Screen with Profile Information

(c) Match Feedback Screen

Figure 2. Research-in-Progress into Passive Context-Awareness in Social Matching Systems

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 [3,7].

As a result we are engaged in ongoing research examining how opportunistic social matching systems could implement *passive context-awareness* to enable opportunities, instead of just identifying them. Figure 2 shows the design of the application we are building to explore this relatively novel approach to opportunistic social matching. It provides users an ongoing stream of potential opportunities to meet interesting people nearby (2a). Users can scan them at a glance on their phone's lock screen and, when interested, tap on it to get more details about the opportunity, such as more personal information about the matched person (2b). After liking or disliking a match, users can quickly select various reasons why (or why not) an opportunity was interesting to them (2c). In future research this will allow us to study why and when users consider a match *opportune*. Systems could inform users about 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*). We believe that passive context-awareness can be a powerful approach to unobtrusively inform users about contextually relevant encounter opportunities nearby, letting users decide at a glance to act on it or ignore it. We are currently implementing such a system and testing it in a field study, which will provide invaluable data on when, where, and how frequent and quick people act on match opportunities [24].

CONCLUSION

This paper explores a proposed framework of *relational, social* and *personal context* 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 offer a range of insights that may be useful to social matching system designers, such as novel approaches on how to operationalize *relational context* based on social network rarity and discoverable rarity. 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.

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