Understanding Group Event Scheduling via the OutWithFriendz Mobile Application

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The wide adoption of smartphones and mobile applications has brought significant changes to not only how individuals behave in the real world, but also how groups of users interact with each other when organizing group events. Understanding how users make event decisions as a group and identifying the contributing factors can offer important insights for social group studies and more effective system and application design for group event scheduling.

In this work, we have designed a new mobile application called OutWithFriendz, which enables users of our mobile app to organize group events, invite friends, suggest and vote on event time and venue. We have deployed OutWithFriendz at both Apple App Store and Google Play, and conducted a large-scale user study spanning over 500 users and 300 group events. Our analysis has revealed several important observations regarding group event planning process including the importance of user mobility, individual preferences, host preferences, and group voting process.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**;

Additional Key Words and Phrases: Group Event Scheduling, Group Decision Making, Collaboration, OutWithFriendz

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1 INTRODUCTION

The ability of users to organize events using mobile devices is a defining characteristic of today's social network systems. With the advancement of mobile technology, more and more people are digitally connected, which makes the analysis of group event planning process and decision making for event organizers critically important. There is a rich history of UbiComp research concentrating on individual user behavior analysis, which treats individual user's data as a singleton. However, social interactions among group members are often ignored, and relatively scant research to date has explored the subject of group event scheduling. Some early work [2, 23] has been confined to in-lab surveys and has not studied the real-world event scheduling process by groups of users, nor the factors that would impact group event decision-making. More recently, a study of university groups using mobile phones was presented [14]. What has been missing to date is a detailed understanding of the process of how groups make a decision to visit a particular place at a particular time using their mobile devices. What factors influence a group's final decision? This paper provides detailed novel insights in the event scheduling process of social groups. We believe that this is an exciting area ripe for exploration by the ubiquitous computing

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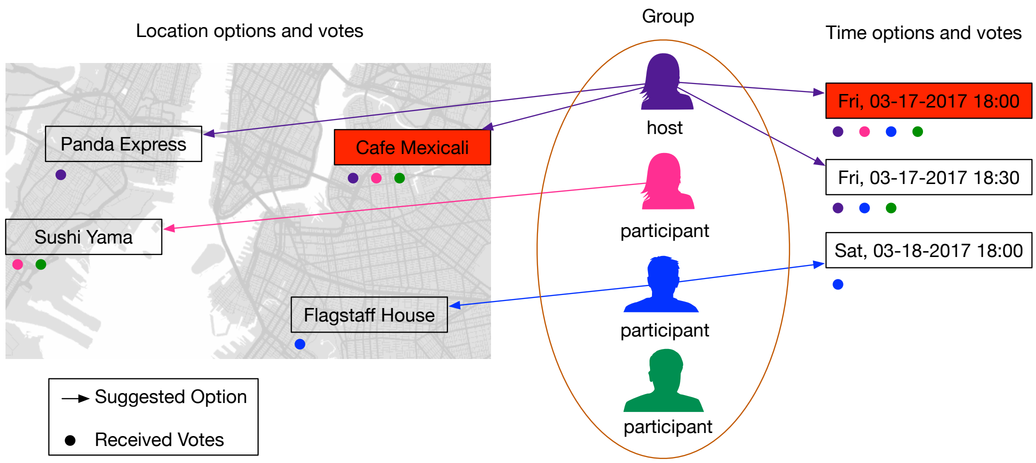


Fig. 1. An illustration of the key elements in our OutWithFriendz system.The colored arrows (dots) indicate which user suggested (voted) for a meeting time or location, and the red boxes indicate the final decisions.

research community. With ever-increasing popularity of smartphones, we expect that mobile computing will be used extensively to assist groups of people in event planning in terms of when and where to rendezvous. Consider a group of friends out on a weekend evening trying to decide what movie to see or where to eat, or consider a group of professional colleagues trying to decide where to go for lunch. Given the frequency with which people schedule colocated events, we believe mobile applications for group event scheduling can provide significant help.

However, despite this considerable potential, today's technology offers limited help when it comes to coordinating group events in online and offline scenarios. Currently there are few group event organization applications on the market. The most commonly used services are Meetup [20], Facebook Events [10] and Evite [9]. In these services, hosts organize offline events and post them on the website. Users or group members who are interested in these events RSVP and later attend the events in real life. However, in all of these existing services, meeting time and location are settled by the host at the creation of the event. Potential users are not able to sufficiently express their opinions on when and where to meet. This will more or less have a negative impact on event attendance. Doodle [6] is an online event scheduling service which supports groups in finding a mutually agreeable meeting time. Participants are able to vote for their time preferences. But all the meeting time options are pre-selected by the host. Group members have no permission to suggest new options. In addition, group members cannot suggest or vote for meeting locations.

To address the limitations of existing services, we developed OutWithFriendz, a mobile application that enables groups of people to decide together through a voting process the date/time the group would like to meet as well as the location where they would like to meet. OutWithFriendz is implemented as a client-server architecture that is comprised of both iOS and Android based clients that communicate with a server implemented as a Java Web application.

The main elements of our OutWithFriendz mobile application are shown in Figure 1. To start using it, a user may create a new invitation acting as a host. During this process, she can specify the details of this invitation including a title, a list of suggested dates, a list of suggested locations and invited participants. After this host submits a new invitation to the server, all invited participants receive it and can view the detailed invitation information on their own clients. They can then suggest more dates, locations or vote for their preferred options and comment on the invitation. After the voting process has ended, the host then decides on the final meeting location and time, which are then sent to all participants. In this example (Figure 1), the host suggested four locations and three date/time options. After the suggesting and voting process, she selected Cafe Mexicali and Friday, 03-17-2017, 18:00 as final decisions, which received the most votes. Please note that, in our design, the host can make decisions based on the voting results, but she does not have to always obey them. We do find few hosts in our field study whose final decisions was different from the options that received most votes. This scenario will be discussed later.

Introducing our newly designed OutWithFriendz mobile application which embeds group decision making into the voting process raises new questions: How do the mobile app users collaborate to organize their group events? What are the major factors that will impact group decisions? How is the voting behavior processed? And how to improve the event attendance rate?

Our mobile application also collects user mobility-related data. The app posts GPS user location traces to the server. Users may opt out from providing their location traces, although most users did not disable location tracking for the entire duration of their participation in the study. This user mobility data provides great opportunity to derive such input factors as spread, movement, mobility, and to investigate their impact on group event scheduling.

The contributions of this paper can be summarized as follows:

- The paper describes the design and implementation of a new mobile application for group event scheduling and its supporting system: OutWithFriendz provides smooth functions for group hosts to easily create an invitation and invite other users to join. All group members can suggest their preferred meeting locations and date/time, and vote for them. The host finalizes meeting location and time based on the voting results.
- The OutWithFriendz system represents the first field-based study of the group event scheduling and decision-making process in the context of a deployed mobile application with widespread geographic usage. This has allowed us to collect precise user traces data.
- Using the data collected from a field study of this novel system, we discovered a series of factors, such as mobility, host preference, user preference, and social voting influence that are significant in group event planning and decision making processes. A correlation analysis of these factors is also performed. Our study offers new insights for group hosts and members to improve their real-life event organization.

The rest of this paper is organized as follows: After discussing the related works, we introduce our system design and data collection. Next we present our data analysis and correlation analysis in more detail. Finally, we summarize the important results, highlight the key findings, discuss their potential usage, and conclude this work.

2 RELATED WORK

In this section, we discuss works that are most relevant to ours. We divide them into three categories.

Group event organization has been studied in a number of recent works. Yu et al. proposed a Credit Distribution-User Influence Preference algorithm to recommend potential participants to the group host [29]. Zhang et al. and Pramanik et al. built models to predict event success in Meetup [24, 30]. The work by Du et al. collected a series of contextual factors to predict individuals' activity attendance [7]. However, all of these works collected their datasets from large public social websites such as Meetup and Douban. In these services, the group host makes the event decision on their own. The meeting location and time are settled when the invitation is created. An interactive group event scheduling process is missing in these services.

Social influence occurs when an individual's emotions, opinions, or behaviors are affected by others. This phenomena has been observed in many domains. For instance, Goyal et al. proposed an influence maximization method based on a historical user action log [12, 13]. Li et al. further incorporated friend and foe relations in social networks for influence maximization [17]. Using a Meetup dataset, Zhang et al. demonstrate the significant impact of group leaders in making event decisions [30]. In the Doodle voting application, Zou et al. find that in open polls, the voting decisions by later respondents are highly influenced by early and nearby respondents [31]. In this paper, we analyze the difference between the impact of the group host and participants on group event planning, as well as the behavior of early and late-coming voters, and how early voters affect late voters, which to the best of our knowledge has not been previously studied.

Our work is also generally related to group behavior analysis. Sen et al. designed a group monitoring system for urban spaces [25], and Jayarajah et al. studied how users' mobility patterns change when they are within a group [14]. Lampinen et al. investigated how users deal with group co-presence to prevent conflictive situations [15]. There are also works studying group colocated interactions using mobile devices [11, 19]. The work by Brown et al. investigated the differences between individual and group behavior with respect to physical locations [3]. However, previous works have limited understanding of how groups schedule and make decisions for events, or the influence of the group host and participants. Our system allows users to easily express their preferences by suggesting and voting for meeting locations and time. By analyzing group event planning process using data collected from our system, we can gain some useful insights for better group event organization.

3 SYSTEM DESIGN

In this section, we describe the design, architecture, and implementation of the OutWithFriendz system. We also present a walk-through example to illustrate the user workflow of our app for group event scheduling.

3.1 System Architecture

In order to understand group user behavior at scale, we designed the OutWithFriendz mobile client for both the iPhone and Android platforms. The mobile client communicates with a remote server, which is implemented as a Java Web application using the Spring Roo application framework [26]. We decided to use Spring Roo because it allowed us to quickly prototype and iterate on the design of the OutWithFriendz app. All required functionalities to the client are exposed through the server's REST APIs. We use MongoDB to store and manage all data on the server [22]. MongoDB is a widely used NoSQL solution which provides high performance, low complexity, and more importantly, native support of geospatial data and queries. To push notifications between server and clients, GCM services are used to handle all aspects of message queueing and delivery to client applications running on both mobile platforms. We also call the Google Maps API to retrieve location search results. Figure 2 shows the overall architecture of our OutWithFriendz system.

3.2 UI Design Challenges

In order to enable a natural group decision-making workflow, we iteratively improved the UI and workflow of the OutWithFriends app based on feedback collected from user studies. We started with an initial usage survey before releasing the app to the market. During our survey, we hired seven students on campus who have different academic backgrounds. They formed three groups to use our app and provided useful feedbacks for improving UI design. For example, these users suggested: (1) Adding a chat board to allow group members to discuss their opinions; (2) Allowing users to edit the location title and provide detailed information for each location; (3) Allowing users to link suggested locations with the Google Places application; (4) Pushing notifications if an invitation is created or modified; and (5) Replacing text buttons with interactive icon buttons. Implementing this functionality helped us improve our app to better support the real-life group event scheduling process. We also added and altered application functionality to improve usability, based on many user suggestions received during application usage. At the beginning of the study, we focused on dining events only. Later we came to realize

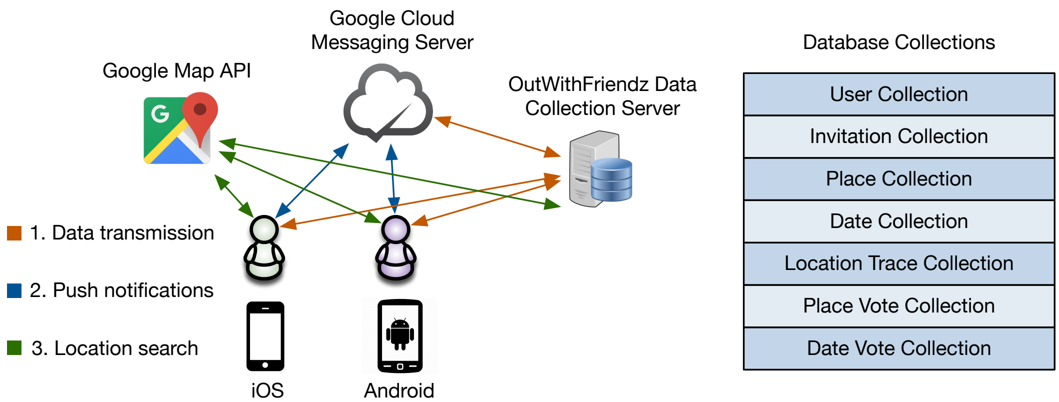
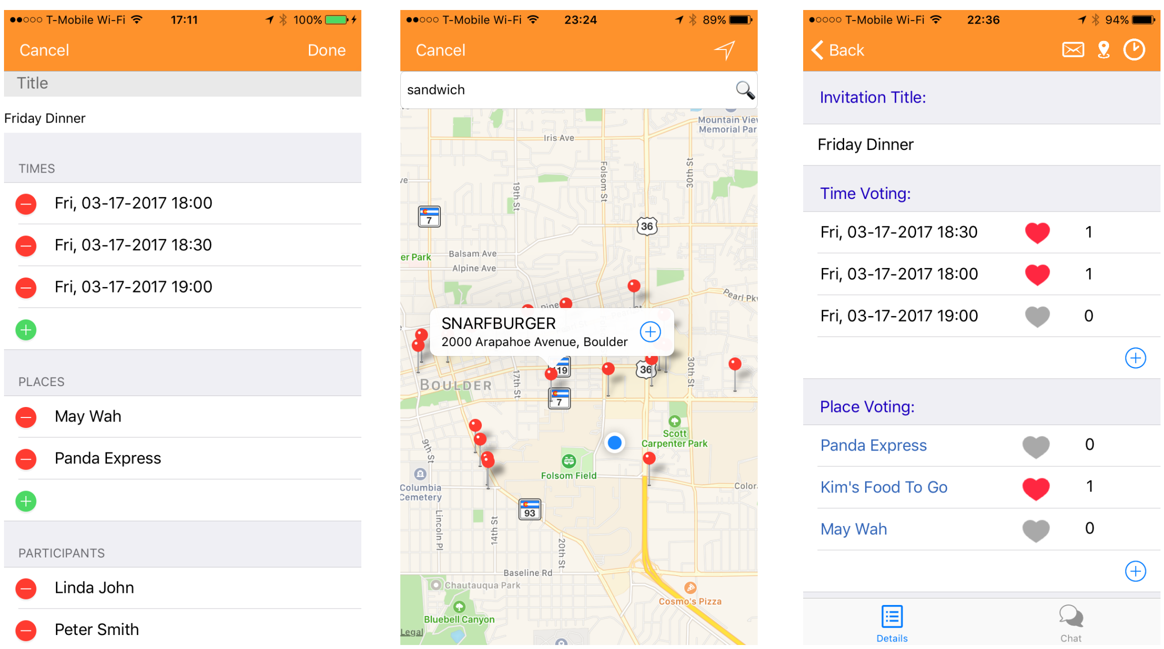


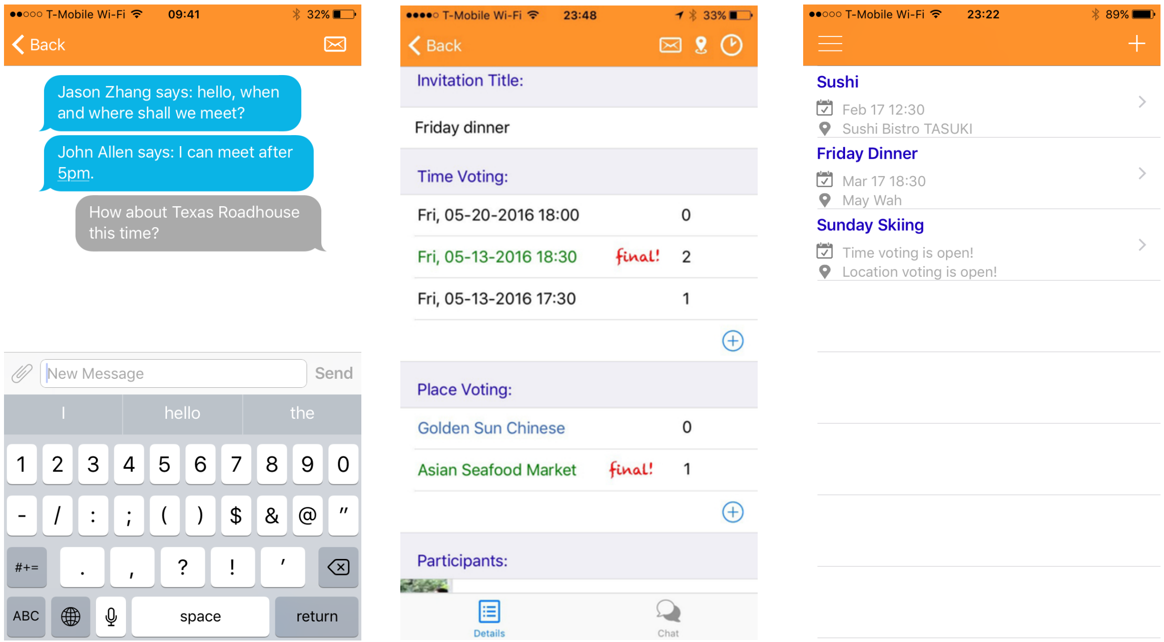
Fig. 2. The architecture of the OutWithFriendz system.



(a) Create invitation. (b) Add location through Google Map. (c) Suggest and vote for preferences.

Fig. 3. Main workflow of the OutWithFriendz mobile application.

that the users would also like to use the OutWithFriends app for generic group gatherings, such as going for a hike or watching a movie. To support this functionality, we shifted from integrating with Foursquare API to the more suitable Google Places API. We also changed the workflow for the voting process to make it more flexible. Initially, invitation participants were required to decide on the meeting time before starting the voting process



(a) Chat screen. (b) Invitation finalization screen. (c) Invitation list screen.

Fig. 4. Main functions of the OutWithFriendz mobile application.

for the location. However, our users preferred to perform time voting and location voting concurrently, which is more flexible. Next, we describe the main workflow of our app.

3.3 A Walk-through Example

To better understand the workflow of our mobile application, we provide a walk-through example of how the main functions are used for group event scheduling.

3.3.1 A host invites two friends to meet for dinner. In this use case, we describe the actions a user would take to invite some friends to meet for dinner. Here we call this user the host. When creating a new event invitation, the host will go to the window shown in Figure 3a and perform the following steps: (1) create a title for the invitation, such as Friday Dinner; (2) specify one or more possible dates and times for the invitation; (3) suggest meeting locations using Google Map Services, as shown in Figure 3b; and (4) add one or more friends that want to be included as participants in the invitation. Finally, when the host is satisfied with the invitation settings, she taps the "send invitation" icon, to send the invitation to all selected participants. She can also start voting for her own preferences right after the new invitation shows up on her screen.

3.3.2 A user receives an invitation to meet several friends for dinner. First, the user receives a notification from the OutWithFriendz application indicating that she has received a new invitation. The user can express her preferences by voting on one or more possible options for meeting dates and locations, as shown in Figure 3c. One important feature of our system is that the user may also add new proposed dates/time or locations to the invitation. Once the user has added a new option, it will be automatically made visible to all other participants. Users are also allowed to change their suggestions and votes throughout the voting process. In the "Chat" tab shown in Figure 4a, the user is also able to send text messages to other group members for discussion and better coordination of the scheduling process.

3.3.3 Host finalizes the invitation based on voting results. The voting process continues until the host decides to finalize the meeting time and location. Only the host is permitted to finalize, which is shown in Figure 4b. After the host has finalized the invitation, each participant receives a notification regarding this action. To support unforeseen changes, the host could still update the final decision after it is finalized. Each user's main screen will show a list of invitations that she has participated in, as shown in Figure 4c.

4 DATA COLLECTION, METHODOLOGY, AND GENERAL CHARACTERISTICS

We first describe the dataset we collected using our OutWithFriendz system and the methodology we used throughout the paper, then conduct data distribution analysis to understand the key characteristics of our dataset.

4.1 Data Collection

We deployed our OutWithFriendz mobile application on the Google Play and Apple Store marketplaces. To collect enough data for group dynamics analysis, we posted advertisements on Microworkers [21] and Craigslist [5] for participants. For teaching these users how to use our app correctly, we also made an introductory video, which is included in our supplemental file: "OutWithFriendzIntroductionVideo.mp4". For each legitimate completed invitation, we paid the host of a group 20 dollars, with the provisions that: (1) The host and participants must live in the US; (2) The host should invite at least two other friends to the invitation using our app; (3) The group must demonstrate a full voting process; (4) The host must finalize the meeting time and location for the invitation; (5) Each participant would open their location services on their smartphone during the study and allow us to track their mobility traces; (6) At least half of the group members attended the finalized event[1].

4.2 Dataset and User Demographics

From these two job post websites, we collected 246 legitimate invitations over a 5-month period from 432 users. In addition, 71 students on our campus used the app without getting any payment, which contributed another 76 legitimate invitations. The whole data collection period spanned from January 2016 to May 2017. In total, 503 distinct users of our OutWithFriendz application were identified, generating 322 legitimate invitations. Figure 5 shows the distribution of all suggested locations recorded in our server across the US. It indicates that our users are widespread in 34 different states and 81 cities throughout the country.

To better understand the demographics of our users, we have conducted an anonymized survey using Google Forms . We contacted all users through their Facebook accounts to complete the survey. In total, 294 of users responded and completed the survey, representing 58.4% of all users. The results are shown in Figure 6. We can see that 60.8% of the users who responded to the survey are female and 48.5% are self-employed. The ratio of self-employed users is high because many users from crowdsourcing websites are freelancers or housewives who have more free time to complete assignments and earn extra money. Students, including some from our campus and some from the Microworker website, account for 27.5% of our participants. In addition, most (83.0%) of our users are young, aged 18-35.

In addition to collecting data about the event organization process, we also collected user mobility-related data. The OutWithFriendz app posts GPS user location traces to the server either every 5 minutes if the app is running in the background or every 30 seconds if the app is running in the foreground. Before participation all of our users were required to provide informed IRB consent. They would turn on the location services on their smartphone during the test so we were able to collect the data. All location traces are anonymized and

[1]We added this requirement to prevent workers from creating fake invitations and making dishonest money. It would be interesting to analyze the low-attendance events, which we plan to investigate when we have more users and events.

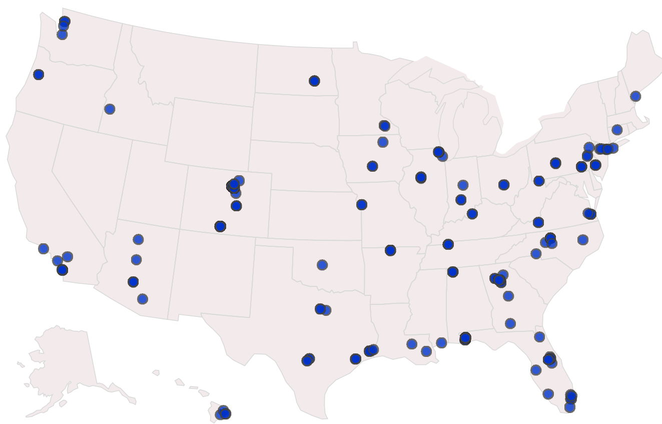


Fig. 5. The geographic distribution of all finalized locations across the US.

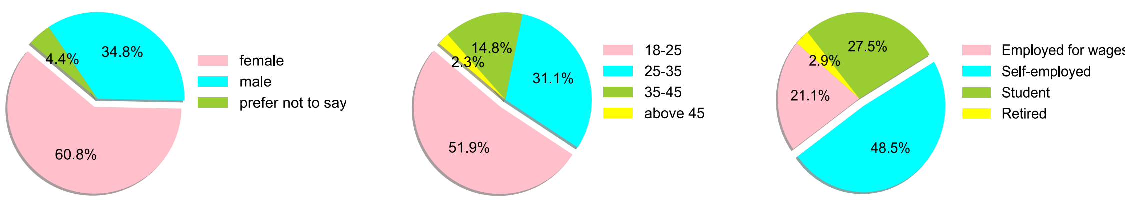


Fig. 6. User demographic information of OutWithFriendz Users (294 participants). (L) Gender distribution. (M) Age distribution. (R) Profession distribution

permission to use this anonymized data is provided when installing the app. The total amount of user traces data collected was about 1.1 GB.

4.3 Methodology

We define some concepts and notations that will be used throughout the paper. In the following analysis, we only use completed invitations in our dataset. A "group decision" refers to the information submitted by the host after an event has occurred, including the final group consensus rating.

In addition, for each event e, we define T_e as the set of suggested meeting times and L_e as the set of suggested locations. For each participant i and option o of event e, we let $V(i, o)$ be an indicator function which indicates whether i voted for option o:

$$V(i, o) = \begin{cases} 1 & \text{Participant } i \text{ voted for option } o \\ 0 & \text{Otherwise} \end{cases} \tag{1}$$

Then we define user's available time and location options as:

$$\text{user } i\text{'s time availability for event } e = \frac{1}{|T_e|} \sum_{o=1}^{T_e} V(i, o) \tag{2}$$

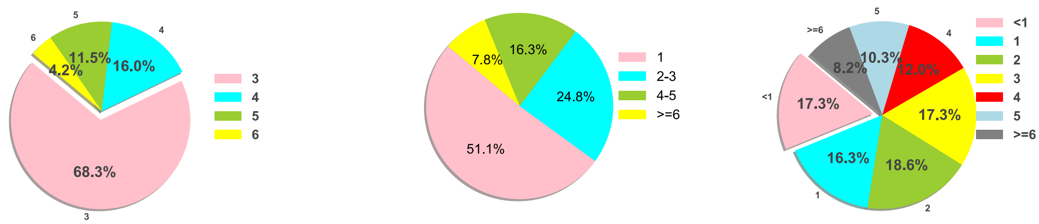


Fig. 7. The distribution of group size (left), event count by host (middle) and number of days to make final decision (right).

$$\text{user } i\text{'s location availability for event } e = \frac{1}{|L_e|} \sum_{o=1}^{L_e} V(i, o) \tag{3}$$

Using an individual user's location trace data, we are able to analyze statistical properties of individual mobility. One way to consider a movement is to calculate the distance between two consecutive location trace points in our dataset. This will result in the detection of many very short movements, such as from one office to another in the same building. However, due to the location services limitation in today's mobile phones, these short movements cannot be traced precisely. For instance, when users are indoors, mobile phones may record false location changes where there was no movement, or miss actual location changes that are small. To eliminate these very short and uncertain movements and extract long movements, we implement an algorithm introduced by Ye et al [28], which was originally designed for GPS data. Assume that each individual's location trace points detected by mobiles devices are ordered by timestamp $L = \{l_1, l_2, l_3, ..., l_n\}$. We identify two types of movements. *Type 1* refers to the short movements of a user within a building. In *Type 2*, the user will travel from one area to another with a significant travel distance larger then r, for some period of time. In our experiments, r is set to 0.12 miles (200 meters) and the period threshold is set to 30 minutes, as suggested by [28]. To extract all the *Type 2* movements and eliminate *Type 1* movements, we iteratively seek spatial regions where the user remains for more than 30 minutes and all the tracked points within this spatial region lie within 0.12 miles. Then the location points in this spatial region are fused together by calculating the centroid of these points. The centroid point is considered as a **stationary point** for the spatial region.

4.4 Group Size Distribution

Figure 7 left summaries the distribution of group size in our OutWithFriendz dataset. Here we define group size as the number of participants who finally stayed in the invitation. We do not count users who were removed from the invitation, either by themselves or by the host, because they did not participate in the whole scheduling process and their votes were not shown after the removal. We observe that most of the groups in our study are small, with the large majority being groups of three. We were pleased to see a significant fraction of groups with five (11.5%) and six members (4.2%) who were able to use the app concurrently. Our work focused primarily on obtaining data for groups of three or more, which we feel represent many typical social group interactions of interest to us. As a result, we did not focus on examining pairwise groups in this study. The figure's trend lines suggest that if we had opened up our study to pairwise groups, then our data would have been overwhelmingly skewed toward pairwise groups. However, now that we have obtained substantial initial data for larger groups, we plan to also explore the behavior of pairwise groups in our future works.

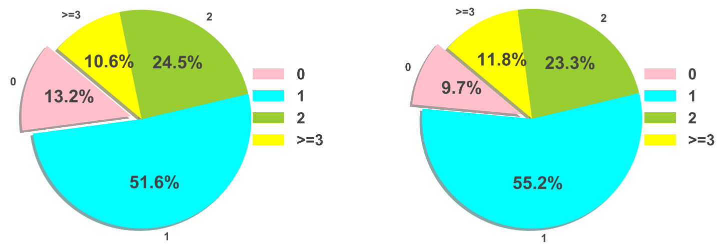


Fig. 8. The distribution of number of votes by a single user for event time (left) and place (right).

4.5 Distribution of Event Count by Host

Figure 7 (middle) shows the distribution of event number created by hosts. Here we only count completed events. During our study, 141 unique users have hosted at least one event, and 72 (51.1%) hosts have created exactly one event each. Please note that each user is allowed to create and join multiple invitations in this study. Moreover, 11 groups (7 from paid users and 4 from students in our university) have used our mobile app frequently, with more than six legitimate invitations per group in our dataset.

4.6 Distribution of Days to Make Final Decision

We are interested in the duration that it took for event organizers to make their final decisions. As shown by the right figure in Figure 7, the number of days to make the final decision is somewhat evenly distributed, and there is no dominant duration in this distribution. This is a bit surprising or counter-intuitive, since we expected that there may be a more pronounced duration of decision-making within the first couple of days of creating an invitation. However, there are also a substantial fraction of events that took four or more days to decide (about 30%), indicating that a large fraction of hosts are taking a long time to decide. This may be affected by the type of events and the amount of lead time. For daily meals, users can make a decision within thirty minutes while for some weekend activities, they will start planning it at the beginning of the week.

4.7 Voting Distribution of Individual Users

Voting distribution is based on the number of votes made per individual user. The distributions for time and place voting are shown in Figure 8. The majority of users will vote for one option as far as the event time. Similarly, the majority of users will vote for one option in terms of the place voting. In both processes, around 10% didn't vote and 10% voted for more than 2 options. This voting behavior is analyzed further in later sections.

4.8 Distribution of the Proportion of the Votes

We also analyze the proportion of users who voted for event time or location in the final decision. The distribution is shown in Figure 9. More than 70% of the final decisions for both time and location received majority votes to become the final choice. This is understandable since groups tend to agree on the majority votes. For the remaining 30%, we observe some very interesting behavior. In these polls, the final decisions did not receive the majority of the votes. In fact, in a small fraction of cases, there is a non-zero proportion of polls in which the final decision received no votes. In these cases, the group host, who is the only one with the power to finalize the event time and location, decided to override the majority voting results, either by personal fiat or possibly through a discussion with other group members that caused them to change their minds.

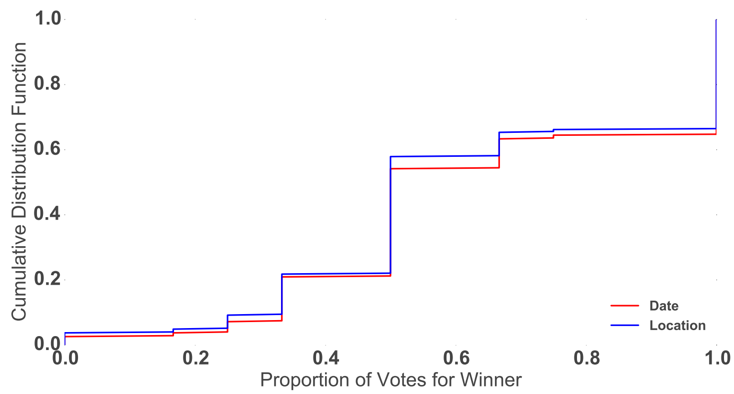


Fig. 9. The proportion of users who voted for final event time (red) and location (blue).

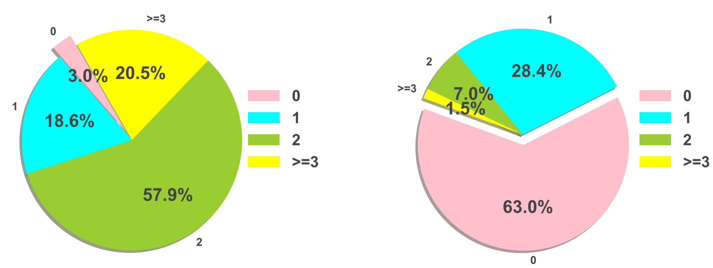


Fig. 10. The distribution of the number of suggestions made by group host (left) and other participants (right).

4.9 Suggestion Distribution

OutWithFriendz app allows group participants not only to vote for their preferences, but also to suggest new options. Figure 10 shows the suggestion distributions for host and participants. Most hosts will suggest 2 or more options for the event. We also observe a small portion of hosts who provide no options of their own, and rely on other group members to provide suggestions. For participants, more than 60% didn't make new suggestions. They just vote for the existing options. Some made one new suggestion while very few of them would make too many new suggestions. We will further compare the influence of group host and participants in our group decision section.

4.10 Metro vs Non-metro Areas

Using the location trace data we collected from our users and the U.S. census data, we are able to identify locations frequently visited by our users. The technique we used will be introduced in detail in Section 5. Then we can project each user's home county using the frequently visited locations. According to the latest Rural-Urban Continuum Codes released in May 2013 [1], every county is classified as a non-metro or metro area. In our dataset, 48% the users live in metro areas and 52% live in non-metro areas[2].

[2]Please note our dataset contains 71 students who lived in Boulder doing this study. If we remove this student population, the proportion of metro and non-metro users would be 39% and 61%, all from crowdsourcing market users.

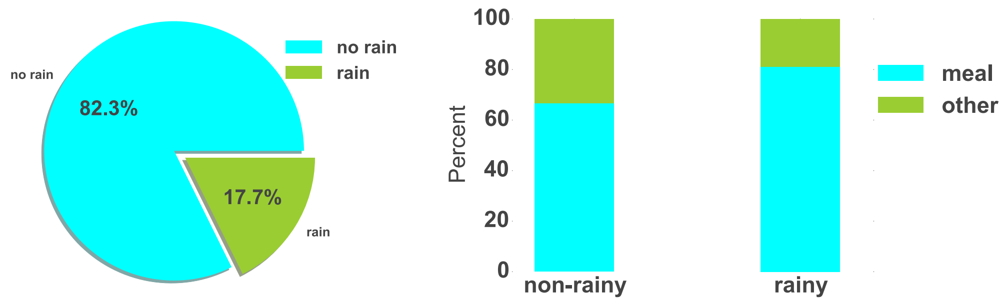


Fig. 11. (L) The distribution of events on rainy days vs. non-rainy days; (R) The distribution of meal events and other events on non-rainy days and rainy days.

4.11 Weather Factor

An important external factor that can influence event organization relates to weather. Here we examine the impact of rain and temperature on our dataset. For this analysis, weather and temperature information for each event was scraped from weathersource API [27] at its location and starting time in our dataset. Note that we can only get hourly weather data from weathersource. If the starting time of one event is 19:35, in the analysis we use 19:00 weather data at the same day crawled from weathersource. Here we decide it is raining if the precipitation of an event's starting time is above 0. On snowy days, usually the precipitation will also be above 0, which we classify as rainy in our analysis.

Figure 11 shows the distribution of events that happened in rainy weather or not. 82.3% of events organized in our app occur in non-rainy weather. There are two reasonable explanations: (1) In many places around the country non-rainy days happen more often than rainy days; (2) Bad weather would have negative influence on real event attendance. Looking deeper, bad weather appears to affect the types of events that are organized. In OutWithFriendz, any place can be added to the Google Map as an option for voting, and need not be confined to a restaurant only. For example, people have used the app to organize events such as outdoor hiking and going to the movies. We divide all events into two category types: meal events and other events. Meal events refer to people hanging out for lunch or dinner, which is the majority event type in our dataset. Other events include activities that are not primarily dining, e.g. sporting and entertainment events. In our study, we found that bad weather would have less impact on meal events compare with other types of events. Figure 11 show that 66.7% of the events belong to meal events on non-rainy weather while this number goes up to 81.1% on rainy days.

5 GROUP DECISION ANALYSIS

The analysis in this section examines the impact of a number of factors on group decision. We divide them into four categories: (1) impact of user mobility, (2) impact of individual preference, (3) impact of host preference, and (4) impact of voting behavior.

5.1 Impact of User Mobility

We now examine the impact of user mobility on group behavior in OutWithFriendz. Here we define user mobility as the total travel distance traveled by a user in the 48-hour period preceding an invitation. Our assumption before was that users who traveled longer distances will be more exhausted, and thus less likely to have significant voting availability. However, our analysis refutes this conjecture:

Table 1. The correlation of user mobility and voting availability

	Pearson correlation coefficient	p-value
The correlation of user mobility and date voting availability.	0.276	7.12e-05
The correlation of user mobility and location voting availability.	0.281	2.92e-06

Table 2. The correlation of group mobility and area's urban density .

	Pearson Correlation Coefficient	p-value
Population density	0.1834	0.013
Housing unites	0.1572	0.018

Observation 1. *Users with higher mobility are more active in attending social events.*

We use the Pearson correlation coefficient [16] to calculate the relationship between user mobility and voting availability. Table 1 shows that the correlation of user mobility with both date and location voting availability is positive, and the results are significant ($p < 0.001$). These results indicate that highly mobile users are more available for event attendance.

Observation 2. *Group mobility has a positive correlation with an area's urban density .*

Given the spatial regions that are detected, we are interested in investigating whether there exists any pattern between a group's mobility and an area's urban density . Our hypothesis is that groups living in metro areas have higher mobility than groups living in non-metro areas, since metro group members may be more spread out in big cities and generate longer travel distances. To perform this analysis, we downloaded the 2016 U.S. area development degree data from the U.S. Census Bureau [4]. Here we use population density and number of housing units to calculate the urban density of an area. For simplicity, we only consider the location of each group event. It is possible that group members live in a city but traveled to a rural area for the event. But this is rare in our dataset. Table 2 shows the relationship between group's total travel distance and the corresponding county's population density and housing units. The Pearson correlation coefficient for these two parameters are positive with p-values that are smaller than 0.05.

5.2 Impact of Individual Preference

To discover underlying factors that may lead users to vote for specific event options, we first focus our analysis on individual users. A social event is typically characterized by two major factors: event time and location. Using the OutWithFriendz dataset we have collected, we first analyze the travel distance between event suggested locations and each participant's closest location cluster, with the requirement that this cluster must contain a point with a timestamp that occurs within 2 hours before or after the finalized time for the invitation. The suggested location options are further divided into two categories: the location options with votes and location options without votes. Based on the results, we make the observation:

Observation 3. *Most users would like to vote for event locations near their frequented locations.*

Figure 12 shows the cumulative distribution of travel distances among locations voted for and not voted for by each invitation participant. The average travel distance for voted locations is 4.19 miles while for non-voted locations is 7.53 miles. A Wilcoxon test found this to be a significant difference ($z = -4.57, p < 0.001$), which indicates users have clear preference to attend events near their frequented places. This is reasonable in daily life. For example, we would intuitively expect that users would prefer to go to dinner at restaurants that are close to their office or home.

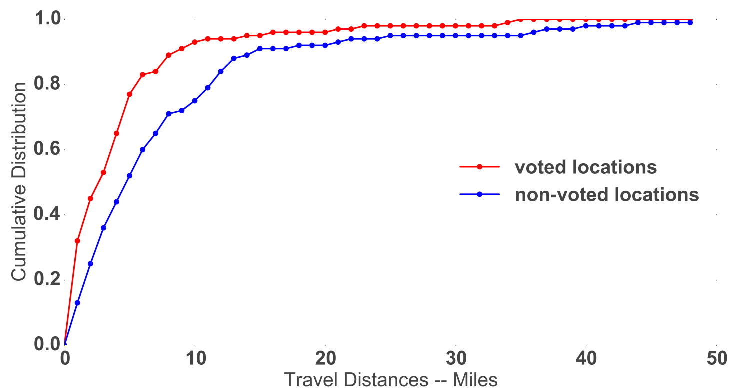


Fig. 12. The cumulative distribution of travel distances among voted locations and non-voted locations for each participant.

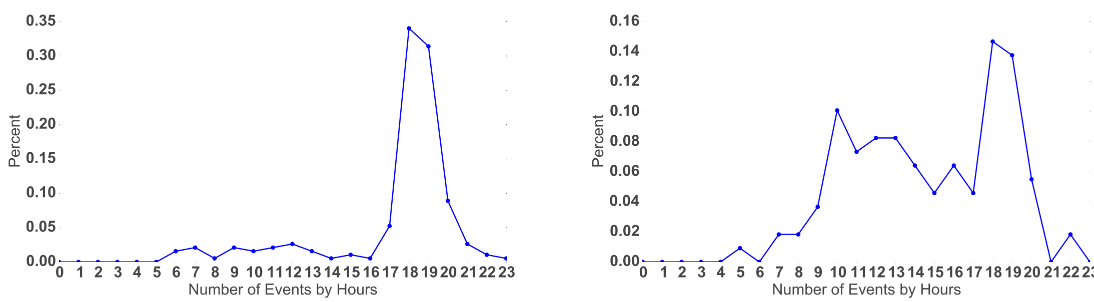


Fig. 13. The distribution of events by hours on weekday (left) and weekend (right).

Observation 4. *People like to attend social events after work on weekdays, while on weekends, events are distributed relatively evenly.*

Additionally, we are also interested in investigating individual user's temporal preference. Our hypothesis is that participants are more likely to attend events after work. Figure 13 depicts the suggested event times on weekdays and weekends. It is clear that in weekdays there is a high spike around 6pm. While in comparison, event times are distributed more evenly throughout the day on weekends.

5.3 Impact of Host Preference

In our OutWithFriendz system, the host has more authority than other participants. The host can not only decide who to invite, but also finalizes the event time and location. This suggests that the host will have more influence on the group decision-making process. In our dataset, we have several significant observations about host behavior.

Observation 5. *The final meeting location is closer to a host's frequented place than other participants.*

It's not surprising that event host would show some "selfishness" when making the final decision. We calculated that the average distance between the final location and host's closest frequented place is 5.23 miles. While the

Table 3. The probability of final event option voted by host and participant

	Probability
Final event date voted by host	0.71
Final event date voted by participant	0.36
Final event location voted by host	0.72
Final event location voted by participant	0.34

Table 4. The correlation between whether host comply voting results and event attendance rate

	Pearson Correlation	p-value
Whether host comply location voting results and event attendance rate	0.48	$< 10^{-10}$
Whether host comply date voting results and event attendance rate	0.47	$< 10^{-10}$

same metric for common participants is 6.75 miles, 29% longer than host, a significant difference according to a Wilcoxon test ($z = -3.38, p < 0.001$).

Observation 6. *The probability that the final event date and location is voted by the host is significantly higher than that for other group participants. For events in which the host did not choose his/her voting option as the final decision, the main reason is to respect the majority voting results.*

Table 3 shows the probability that final event option is voted for by the host and by another participant. It is clear that the final option is much more likely to have been voted for by the host than by other group members, with a probability of 0.71 vs 0.36 for the final event date ($z = -13.22, p < 0.001$). and 0.72 vs 0.34 ($z = -11.87, p < 0.001$) for the final event location. We also observe that among all the invitations in which the final event time was not the host's voting option, 95.2% coincided with the majority voting results. The percentage is 94.4% for the final event location. This indicates that, although hosts have a higher impact on making decisions, they still highly respect other group members' opinions.

Observation 7. *The host choosing not to use the consensus voting result as the final decision would have negative influence on the event attendance rate.*

In our OutWithFriendz application, the host can select a final decision that is contrary to the voting results. According to our user study, there are two main reasons for this behavior: (1) The option that received most votes is not suitable for the event host; (2) the users discussed through using the app's chat function and some members changed their minds but did not update their votes. In our OutWithFriendz dataset, 7.3% of final dates and 9.2% of final locations are contrary to voting results. We calculated the Pearson correlation between whether the host complies with the consensus opinion and the corresponding event attendance rate. The results are shown in Table 4. The positive correlation is significant here for both location voting and date voting. These results confirm that for event organization, hosts that don't comply with voting results have negative impact on the attraction of participants.

5.4 Impact of Voting Process

Voting is one of the most innovative aspects of our OutWithFriendz system. In contrast to traditional online event organization services, such as Meetup and Douban Events, where the meeting location and time is decided only by group host when the invitation is created, OutWithFriendz allows all group members to express their preferences through suggestions and votes. After all invitees have responded to the poll, the group host is able to

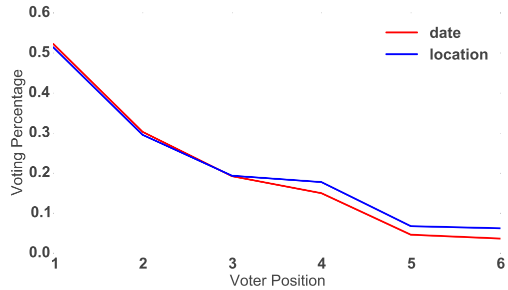


Fig. 14. The relationship between average availability and voter position.

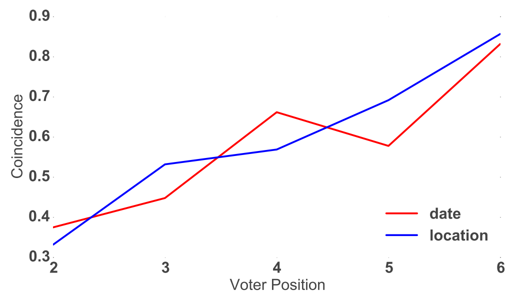


Fig. 15. The relationship between average voting coincidence and voter position.

find a mutually agreeable location and time that usually accommodates most of the group members. Tracking the group's voting process using our system offers a great opportunity to study group decision making behavior.

Observation 8. *Early voters tend to vote for a wide variety of options, while later voters are more likely to report limited availability.*

Figure 14 shows the relationship between group members' average availability and their "voting position". A user's availability is defined by Equations 2 and 3. Voter position refers to the temporal index of casting votes within the scope of an invitation. The host's position is 1, the first voter's position is 2, and so on. There is a clear decrease of availability as voter position increases, and this result is consistent for both location voting and time voting.

Observation 9. *Late voters tend to vote for options that align with existing voting results and are mutually agreeable.*

Due to the fact that new voters can observe other voters' responses, these early responses would easily affect future voting behaviors. In our dataset, we find that later voters are more willing to vote for options that coincide with existing voting results, which makes it easier for the host to find common mutually agreeable options. Here we define the voting coincidence by cosine similarity:

$$Coincidence = Cosine(\vec{v}, \vec{e}) \tag{4}$$

where $\vec{v}$ refers to the new voter's voting vector, and $\vec{e}$ refers to the existing voting vector. For example, if there are four date options in invitation i, and they receive 1, 3, 1, and 0 votes respectively, then the $\vec{e}$ is $[1, 3, 1, 0]$. If a new voter v votes for second, and fourth option, then $\vec{v}$ is [0, 1, 0, 1]. The coincidence here is the cosine similarity between $\vec{v}$ and $\vec{e}$, which is 0.640. Figure 15 shows the relationship between average voting coincidence and voter position. It is clear that there is a positive relationship between voter position and coincidence in both date voting and location voting. Later voters will try to consider their options in light of the whole group's voting behavior. Sometimes, these later voters may vote for less convenient options in order to make the host's life easier.

6 DISCUSSION

In this section, we summarize the key results of our analysis and provide insights into how these results can be utilized for better group event planning experiences. The results cover the impact of user mobility, individual preference, and the host preference on the group event scheduling process. We also discuss the impact of user behavior during the voting process.

User Mobility. The analysis in Section 5.1 showed that users with higher mobility are more likely to be active participants in group events. They are more active in voting for proposed event location and event time. There are two reasonable explanations for this phenomenon:

- Previous studies have shown that users who travel by car, bus, and foot in daily life differ substantially in their value of time, in both revealed-preference and stated-preference surveys [8, 18]. In our OutWithFriendz dataset, the users who travel long distances may travel by car. This increases their likelihood of attending events far away from their frequented spots.
- Users who have higher mobility are more likely to be active event attendees. They are used to meeting with friends after school or work, which results in longer travel distances. Conversely, office workers who sit at their desks during the day have little mobility detected, but may still be tired after work and less likely to travel.

One way to use this observation for better event planning would be to recommend more diverse locations and dates for highly mobile users, as they tend to be more willing to explore new options. On the other hand, users with less mobility should not be overwhelmed with a large number of choices. In addition to recommending event locations and time, this observation can be used for forming groups by matching users with similar mobility levels in the same group, which can lead to smoother event planning experiences.

Individual Preference. The analysis in Section 5.2 revealed typical patterns related to individual preferences for event time and locations. First, with regard to event location, users tend to arrange events at nearby locations to avoid traveling long distances. Second, with regard to event time, on weekdays, users want to schedule events after their working hours, while on weekends users show more flexibility. These observations are worth considering for smarter group event planning. For event locations, the application could suggest places such that the mean travel distance for the group members is minimized, so as to provide a reasonable compromise for the whole group. Likewise, suggested event time should occur outside of typical working hours of the group members.

Host Preference. The results in Section 5.3 show that group event planning is heavily influenced by the host who creates the invitation. From the analysis in this section, it is evident that the final event location is on average closer to the host's frequented locations than that of other group members. We also see that the final event locations and dates are more likely to be the options voted by the host. However, the influence of the host can also lead to negative outcomes: when the host chooses not to follow the group's consensus, event attendance is reduced. These effects point to the need to carefully consider the preferences of the host, and how these preferences align with the preferences of the group, when providing recommendations to event participants. Effective communication mechanisms between the host and the participants should also be provided.

Voting Analysis. The analysis in Section 5.4 shows that the votes cast by early voters are very likely to affect late voters. Late voters tend to vote for fewer options, and these options tend to match those that have already received votes from early voters. There are several possible explanations for this observation:

- People who came to the poll later may be busier than early voters, and had a smaller time window before the actual event time, thus their availability is more limited compared with early voters.
- The polls in the OutWithFriendz application are all open polls, which means later voters can see the current voting results. Their votes may not be able to change the current status significantly because every voter can only vote once for a given option.
- Late voters will vote only for agreeable options that help the host to more easily finalize decisions.

This phenomenon can be used to improve the event planning experience. For example, we could encourage users to vote early, so that their votes will carry more weight. We could also hide existing voting results, so as to prevent existing votes from biasing later voters, and facilitate the voting process by providing voting recommendations to users based on their historical voting patterns.

7 CONCLUSION AND FUTURE WORK

In this paper, we have presented the results of a large-scale study of OutWithFriendz, a newly designed mobile application for group event scheduling. We summarize our key findings as follows: (1) User mobility has a significant impact on group event attendance. (2) Users would like to vote for locations near their frequented places. On weekdays, they would like to meet after work while on weekends, they have wider time options. (3) A group host has a higher impact on the group decision making process than other members. (4) Early voters are more likely to vote for more options while late voters tend to coincide with existing results to find a mutually agreeable option. We believe the results presented in this paper are a good start towards better understanding of group event scheduling behaviors in real life.

We plan to pursue several directions for future work. First, although we have collected more than 300 completed group events, we hope to grow our user base through more effective advertising, so that we may achieve viral adoption and gather data at even larger scales. Second, to obtain a user's friend list, OutWithFriendz currently only allows users to log in through their Facebook accounts. Users may want to invite people who are not already a Facebook friend or do not use Facebook at all. This limits our app's ability to support larger groups. We plan to design an "Add Friend" function which enables users to log in and connect with other users directly within the application. Third, currently, polls in OutWithFriends are designed to be open polls, allowing late-coming voters to see existing voting results, which may influence their own votes. We plan to add a closed poll option. For closed polls, existing voting results will be hidden from new voters. This functionality will allow us to examine how a closed poll mechanism influences the group event scheduling process. Lastly, we have seen from our work on OutWithFriendz that a number of factors influence group decision making. We believe that group context can be seen as inhabiting a latent trait space, similar to how users inhabit a latent user trait space in the matrix factorization framework for individual recommendation. Furthermore, our work has revealed that both host and individual members within a group play an important role in the group event scheduling process. In our future work, we intend to pursue the development of a group recommendation system that incorporates these ideas into a probabilistic model for group preferences and make group event recommendations in real-world settings. This will help us gain a better understanding of group event dynamics and provide useful suggestions for group event organizers.

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