Understanding Social Influence Using Network Analysis and Machine Learning

by

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Abstract

If we are to enact better policy, fight crime and decrease poverty, we will need better computational models of how society works. In order to make computational social science a useful reality, we will need generative models of how social influence sprouts at the interpersonal level and how it leads to emergent social behavior. In this thesis, I take steps at understanding the predictors and conduits of social influence by analyzing real-life data, and I use the findings to create a high-accuracy prediction model of individuals' future behavior.

The funf dataset which comprises detailed high-frequency data gathered from 25 mobile phone-based signals from 130 people over a period of 15 months, will be used to test the hypothesis that people who interact more with each other have a greater ability to influence each other. Various metrics of interaction will be investigated such as self-reported friendships, call and SMS logs and Bluetooth co-location signals. The Burt Network Constraint of each pair of participants is calculated as a measure of not only the direct interaction between two participants but also the indirect friendships through intermediate neighbors that form closed triads with both the participants being assessed. To measure influence, the results of the live funf intervention will be used where behavior change of each participant to be more physically active was rewarded, with the reward being calculated live. There were three variants of the reward structure: one where each participant was rewarded for her own behavior change without seeing that of anybody else (the control), one where each participant was paired up with two 'buddies' whose behavior change she could see live but she was still rewarded based on her own behavior, and one where each participant who was paired with two others was paid based on their behavior change that she could see live. As a metric for social influence, it will be considered how the change in slope and average physical activity levels of one person follows the change in slope and average physical activity levels of the buddy who saw her data and/or was rewarded based on her performance. Finally, a linear regression model that uses the various types of direction and indirect network interactions will be created to predict the behavior change of one participant based on her closeness with her buddy.

In addition to explaining and demonstrating the causes of social influence with unprecedented detail using network analysis and machine learning, I will discuss the larger topic of using such a technology-driven approach to changing behavior instead of the traditional policy-driven approach. The advantages of the technology-driven approach will be highlighted and the potential political-economic pitfalls of implementing such a novel approach will also be addressed.

Since technology-driven approaches to changing individual behavior can have serious negative consequences for democracy and the free-market, I will introduce a novel dimension to the discussion of how to protect individuals from the state and from powerful private organizations. Hence, I will describe how transparency policies and civic engagement technologies can further this goal of 'watching the watchers'.

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Thank you especially to my parents who have always believed in me (except for that one time when my mom legitimately thought I was going to fail 4th grade).

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Chapter 1

Introduction

The goal of this thesis is to understand how incentives can be used to change individual behavior with a focus on

1. introducing a technology-driven incentive system (chapter 1) that performs better than the current traditional incentive paradigm and
2. quantitatively analyzing the predictors of success of the technological alternative and building a model of individual-based behavior change (chapter 2),
3. discussing the limitations of the current policy-driven approach and describing the advantages of a technological alternative 1 (chapter 3),
4. providing solutions to the socio-political problems associated with the implementation of the technological alternative (chapter 4)

Before the technology-driven alternative is introduced, it is important to understand how policy-driven approaches are used to change behavior. Policy-driven initiatives that are used to change behavior do it though four general mechanisms: information dissemination, infrastructure opportunities, incentives and sanctioning through prohibition [1]. A more detailed explanation of each four categories follows:

1. Incentives: monetary or material benefits or deterrents such as subsidizing gym memberships to decrease future health care treatment costs

2. Prohibition: rules that allow or prevent certain types of behavior such as banning sugary drinks to decrease diabetes

3. Information: awareness about the risks and benefits of behaviors such as through sponsoring school programs to teach young students about the benefits of a physically active lifestyle

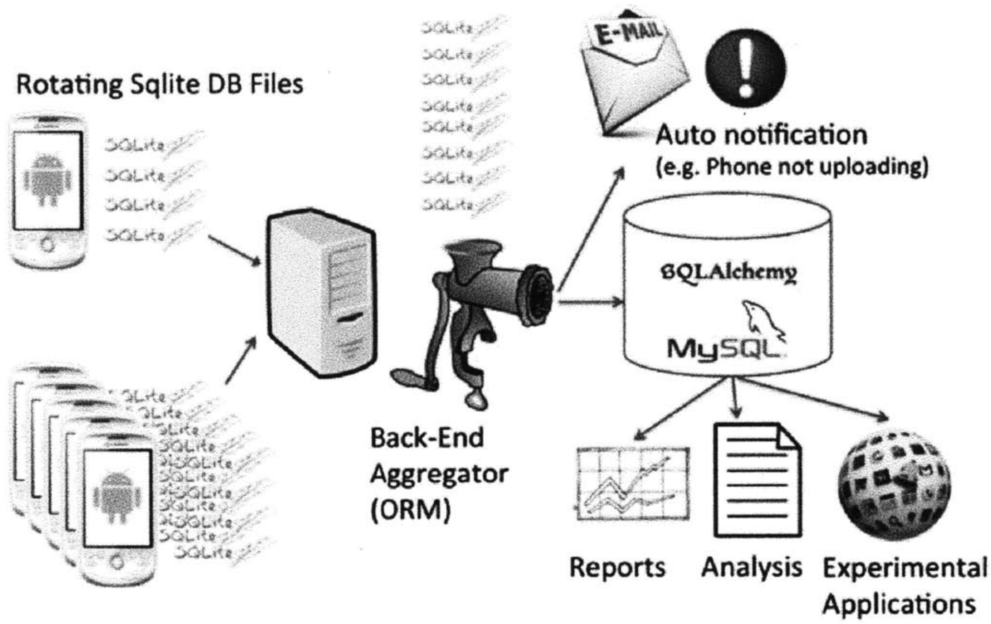
4. Opportunities: infrastructure needed for making behavior change possible, such as building more bike lanes and running paths so people can exercise more.

Each of these policy mechanisms has limitations that can be attributed to two broad groups of issues. On one hand, there is the psychological shortcoming of the intervention in terms of its lack of ability to modify the decision making processes internal to each person: for example, incentives have been shown to maintain and encourage behavior that has already been changed, but has limited effect on initiating the behavior change [1]. On the other hand, there are the institutional, social and political pitfalls of designing or implementing the policy and its intervention in terms of equity and efficiency. For example, incentives to change physical activity can be used by insurance companies to filter out unhealthy people for increased profits, leading to an issue of equity as unhealthy people will be cut off from the service of medical insurance. Another example of bad policy is that of prohibiting private car driving to encourage residents to use public transportation even though the public transportation is unreliable and expensive.

1.1 The Funf intervetion

To minimize the previously-mentioned psychological and institutional failures of the above four categories of policy-driven interventions, a radically different technological approach to changing human is proposed: the Friends and Family Study (funf) [2] undertaken by the Human Dynamics group at the MIT Media Lab in 2010 is a novel experiment in which cellphones were given to students at a leading university in exchange for tracking all their digital information - GPS location, Facebook feed,

Figure 1-1: The system architecture behind the funf intervention



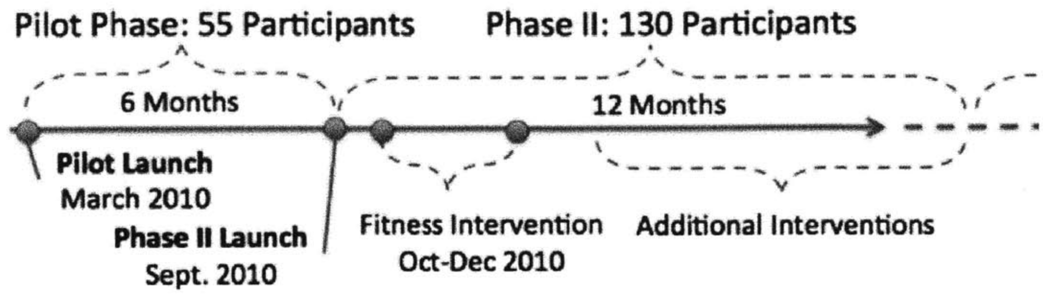
accelerometer data, etc. A complex architecture was designed that collected user's data with the permission and sent it to a centralized server for analysis as shown in the figure below [2]:

The study was run for a period of more than one year (as shown in the figure below).Additionally, the group ran a live intervention on the subjects where the participants were paid based on their increased physical activity that was determined from their daily phone accelerometer values. There are two parts to this intervention, both of which are novel: first, the incentive was built such that it harnesses the subjects social network pressure and, secondly, data was being collected and analyzed in real time to calculate rewards and change the behavior of people. Several variants of the experiment were run in parallel:

1. Paying people based on their own increased physical activity: the traditional incentive paradigm (referred to as control)

2. Paying people based on their own increased physical activity while they were able to see the activity of two of their communicated peers (referred to as peer-

Figure 1-2: The different phases of the funf intervention



see)

3. Paying people based on communicated buddies performance (referred to as peer-reward).

The results of the study showed that here was a clear increase in physical activity of 111% in the peer-see intervention variant and 247% in the peer-reward intervention variant as compared to the control intervention [2], indicating that harnessing the power of social pressure yields much higher behavior change per unit dollar that the traditional policy-driven incentive structure in which individuals are paid based on their own performance.

These results bring about three questions:

1. What are the underlying reasons why this new technological approach works better than the traditional policy-based intervention? Specifically, what are the predictors of success within the new technological approach?

2. What are the political-economic advantages and limitations of this new technological approach compared to the traditional policy-based intervention?

3. What solutions exist to prevent the political-economic issues associated with implementing such technology-driven initiatives?

While the last two questions will be discussed later in this thesis, the first question above will be investigated analytically and quantitatively as part of the next chapter. Before diving into an analysis of the underlying reasons behind the success of this new technological approach, past research was reviewed to inform the choice of analysis performed. Past work on the interpersonal nature of social influence, the importance of weak ties and indirect communication, and long-term behavior change suggested that these aspects of the question are important. Summaries of each of these aspects as to why the technology-driven approach performed much better than the policy-driven approach are presented in the next section.

1.2 Motivation for Analysis

1.2.1 Social Influence

The literature on social influence is vast and covers aspects of social influence ranging from the individual cognitive effects to the greater political-economic implications to society. Since much of the psychological and cognitive aspects have already been covered previously [3], I will focus more on how communication offers a pathway for social influence to occur. The aim of understanding the relationship between social influence and communication is to build better incentive systems that harness social interaction. This is especially important because the richness of electronic social communications email, Twitter tweets, Facebook messages, calls, SMS, etc is yet an untapped gold mine of information that could be harnessed to improve the efficiency of market structures and political-economic incentives systems.

According to Wells and Petty (1980) [4], work in attitude change has emphasized the manner in which persons process the information contained in persuasive communications. This suggests a link between interaction and influence where the idea is that the more two individuals interact, the more one can convince the other. Communication is a complex phenomenon with many dimensions such as frequency, duration, intensity, intentionality, etc. As detailed by Wells and Petty (1980) [4], there have been many studies about these different dimensions of the communication, such as source credibility, distraction, forewarning, message comprehensibility, number of arguments employed, message repetition, issue involvement, counterarguments, favorable thoughts, and anticipated discussion.

Previously, communication as a means for social influence was assessed qualitatively: hand annotations such as 'Bill talked more to Susan during this session' or 'Joe was very angry and always yelled at Jane', anecdotal incidents, repeated head nodding from the audience [5]. More recently, devices were built to record communication between people such as the Sociometer, IR transceivers, radio frequency scanners, the wearable badge Active Badge, visual feedback from LEDs and LCD displays, the iBadge for children, and lastly the Sociometric Badge which is still in use [6]. Although these devices have been the source of considerable breakthroughs in the understanding and modeling of social influence, communication can now be more pervasively recorded and analyzed live though the use of smartphones. Consequently, the funf platform was invented as a means to automatically and seamlessly harness and analyze communication patterns from cell phones [2].

Hence, in this thesis, instead of looking at the different dimensions within communication, I will be focusing on the effect of different modes of interaction as pathways for social influence. The types of interaction in focus will be SMS and call, physical proximity as measured by Bluetooth co-location scans, and finally self-reported friendships. These modes of communication have been chosen partly out of convenience because they are the collected information from the funf platform and partly because they are increasingly seen as essential features of physical and electronic social network interaction. Each of these modes of interaction will be investigated as quantitative predictors of behavior change and hence social influence with the aim of testing their power as pathways of social influence, and with the goal of building better incentives to changing behavior.

1.2.2 Indirect communication and weak ties

As seen in the previous section, communication is an essential pathway to social influence. Instead of focusing exclusively on direct interaction between two actors trying to influence each other, this research will aim at also incorporating indirect interaction between actors. Because the importance of indirect communication has not received enough formal attention in the past [7], and given the breadth of depth of recorded real-world network interaction in this study, indirect interaction will be investigated in this thesis.

Sometimes, the shortest path between two agents is an indirect one [7]. This can happen if given a weighted network, the sum of the distances between A and C and C and B is much shorter than the distance between A and B. Within our framework of investigating the relationship between indirection interaction and social influence, a similar situation could happen: the sum of the strength of the interaction between A and C and C and B is much larger than the strength of the interaction between A and B. For example, A and C and C and B are much closer friends than A and B, so if A wants to influence B, it would be more effective for her to influence C who would then influence B. Examples in the real world such as a manager who talks to each of two employees much more frequently than they talk to each other, or a parent who talks to each of two adult children much more frequently than they talk to each other [7] indicate the pervasiveness and importance of indirect connections between agents.

This is important in our study because even though some of the participants in the funf intervention might not be connected, they might still be influencing each other. Consider this hypothetical situation: two participants in the study might not be directly connected because they might have never called each other or might have never met. However, they still have common group of friends and hence have an indirect link. This is especially relevant if they have been assigned by the study to influence each other. Because I do not want to make the wrong assumption that they have no link even though it is only indirect through one or more common friends, I need a way to compute this indirect interaction. One such way of measuring direct and indirect interaction is through a network metric called the Burt Network Constraint which will be explained in detail in the next chapter.

1.2.3 The importance of long-term behavior change

One critical aspect of determining the success of an incentive mechanism is whether the behavior change induced during the intervention period is retained after the intervention is over. Long-term effectiveness of intervention also known as stickiness - is important for two reasons: because incentive mechanisms are expensive and hence cannot be applied indefinitely, and because the goal of many incentive mechanisms is to achieve long-term behavior change such as in the case of weight-loss diets and smoking interventions.

There are many examples in literature that question the ability of traditional incentive mechanisms to achieve long-lasting impact: the case of seatbelts [8], weight-loss maintenance [9] and physical activity [10]. Previous research shows that less than 10% of people keep a 5% loss from starting weight after 5 years and that Most studies assessing long-term weight loss maintenance have yielded disappointing long-term results [9]. In another study, even the most intensive interventions including motivational interviews and vouchers for access to leisure activities over a period of up to twelve weeks was not effective in causing long-term behavior change of physical activity [10], demonstrating how hard it is to change physical activity behavior in the long term.

As previously demonstrated by Nadav et al. (2011) [2], harnessing the power of the social network by adding a social dimension to incentive mechanisms can produce a large change in behavior during the intervention. This observation as to the success of social incentives will also be investigated for long-term behavior change, especially because data is available about the behavior of participants long after the intervention ended. My hypothesis is that social incentives are also successful at maintaining long-term behavior change because the same interaction pattern and friendship exists after the intervention ended, leading the continuous enforcement of the new norm of increased physical activity. This hypothesis will be confirmed to be true.

Chapter 2

Analysis and Discussion

2.1 Network Analysis

As discussed previously, the amount of interaction between two nodes in a network both direct and indirect is a measure of how much social influence a source node can exert on a target node because the more resources a 'source' agent spends on a 'target' agent, the more the source can influence the target. There are two parts to this analysis which will be implemented in the next section:

1. that interaction is a good measure of social influence

2. that including indirect interaction through neighbors in addition to direct interaction between the source and target is a better measure of interaction.

In the following section, the Burt network constraint will be calculated for several types of interaction: Bluetooth, SMS, calls and self-reported friendship.

2.2 Burt Network Constraint

Burt (2004) [11] defines the network constraint index C_{ij} as the proportion of i's network time and energy that directly or indirectly involves j and the the extent to which manager is network is directly or indirectly invested in the managers relationship with contact j:

$$C_{ij} = p_{ij} + \sum p_{iq}p_{qj} \quad q! = ij, \quad q \text{ in } V_i \bigcap V_j \tag{2.1}$$

where

$$p_{ij} = \frac{(a_{ij} + a_{ji})}{\sum(a_{ik} + a_{ki})} \quad k \text{ in } V_i, \quad k! = i \tag{2.2}$$

In other words, the more a source node in a network and the source's neighbors invest resources in a target node, the higher the network constraint. C_{ij} be calculated for each type of interaction.

Network representation of each type of interaction was built from self-reported friendship surveys, and logs of call, SMS and Bluetooth interaction. Force-directed network visualizations of the different types of interaction are shown in figures 2-1 to 2-4. The dense clustering within the network indicates that some nodes interact more with others within the same cluster than with outside nodes. The amount of interaction between nodes of interest funfit participants was then calculated by applying equation (2) to each interaction network.

Shown below in figure 2-5 are histograms representing the distribution of Burt network constraint for each different type of interactions.

2.3 Measuring behavior change

The time series of accelerometer data for each funfit participant was used to calculate the change in amount of physical activity, which is used as a measure of behavior change.

Two measures of behavior change were calculated by running a linear smoothing regression over each of the following periods for each person's accelerometer data:

1. before the intervention was officially announced yet data was being gathered,

Figure 2-1: Network Visualization of SMS interaction network

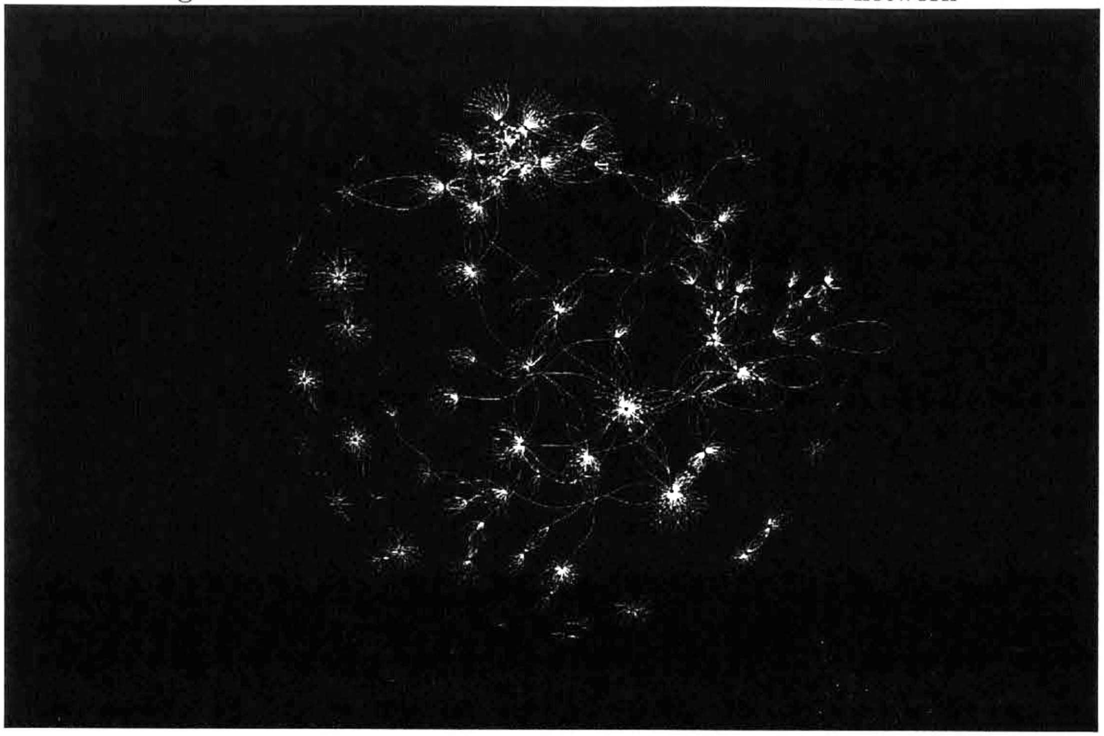


Figure 2-2: Network Visualization of Bluetooth interaction network

Figure 2-3: Network Visualization of self-reported friendship network

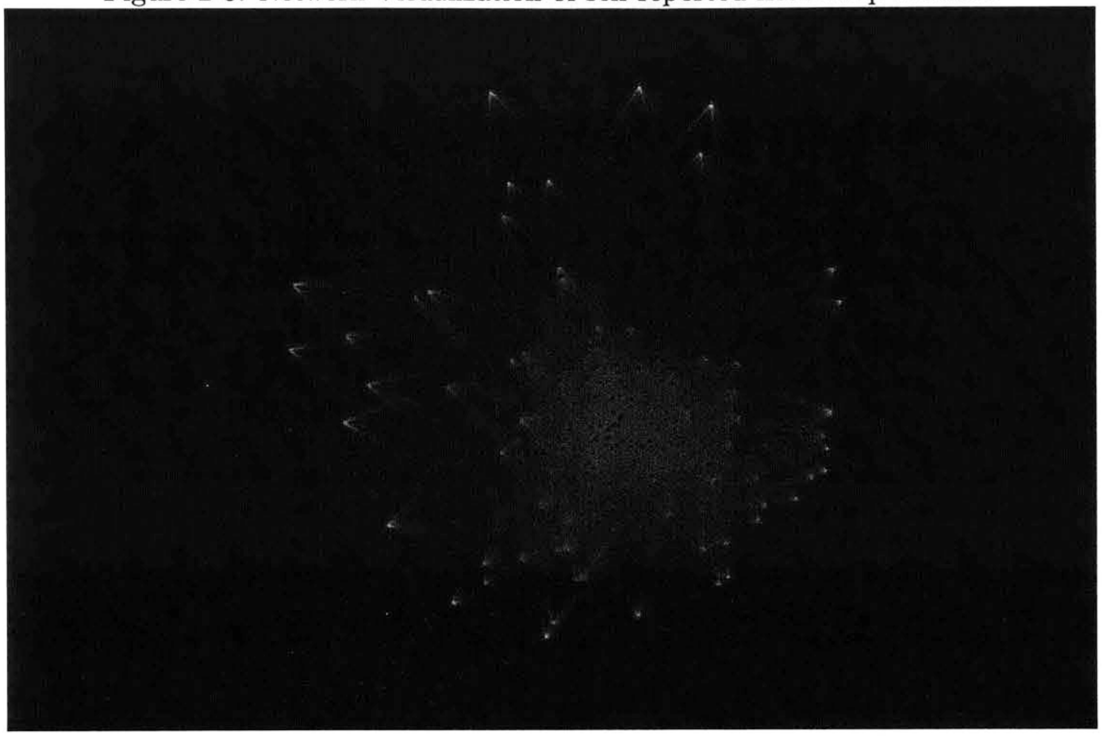


Figure 2-4: Network Visualization of calls interaction network

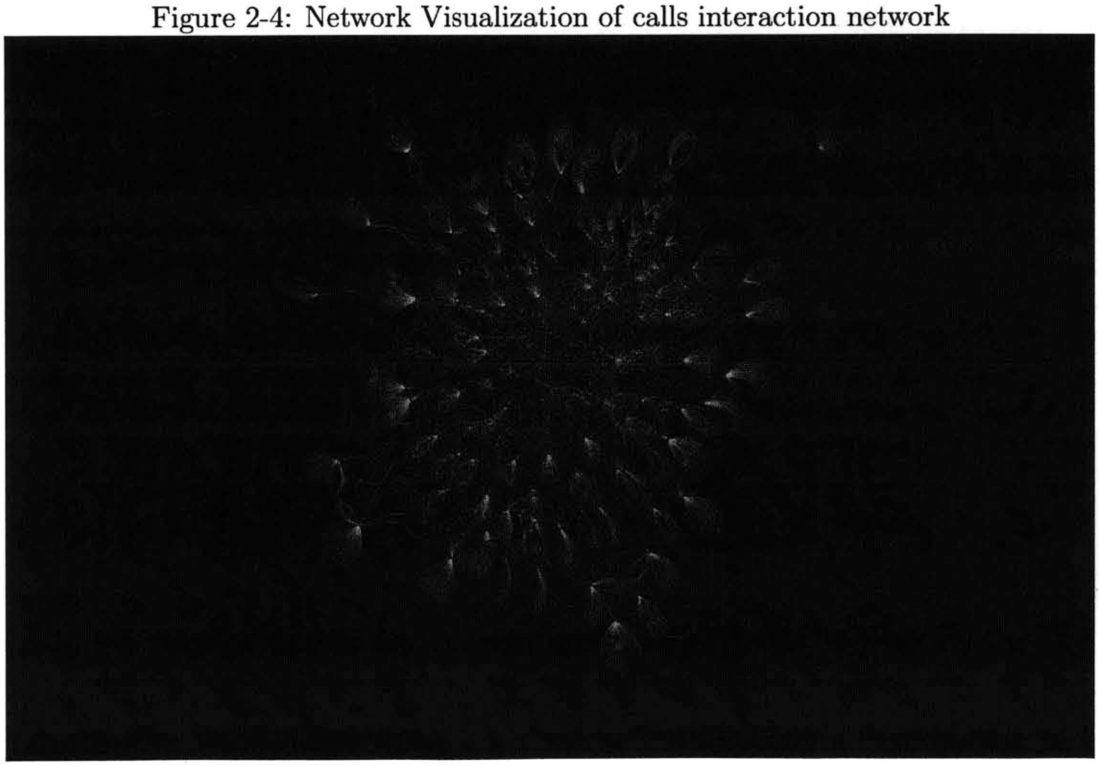
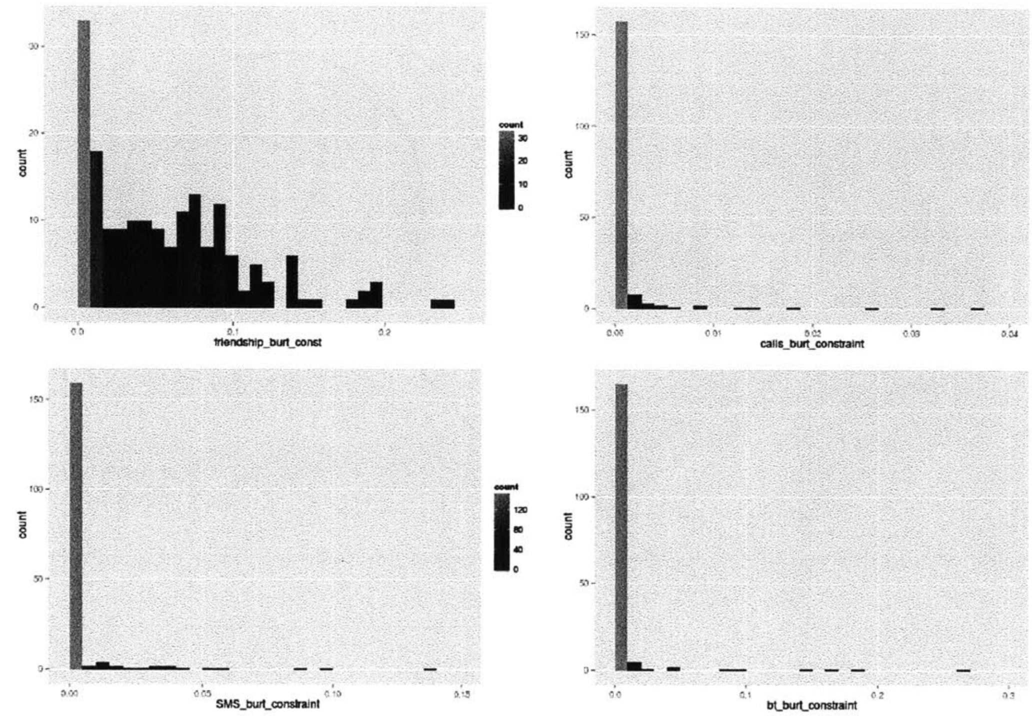


Figure 2-5: Histograms of different Burt network constraints



2. after the intervention was announced (using the second half of the intervention so that the regressions is unaffected by novelty effects), and

3. after the intervention ended.

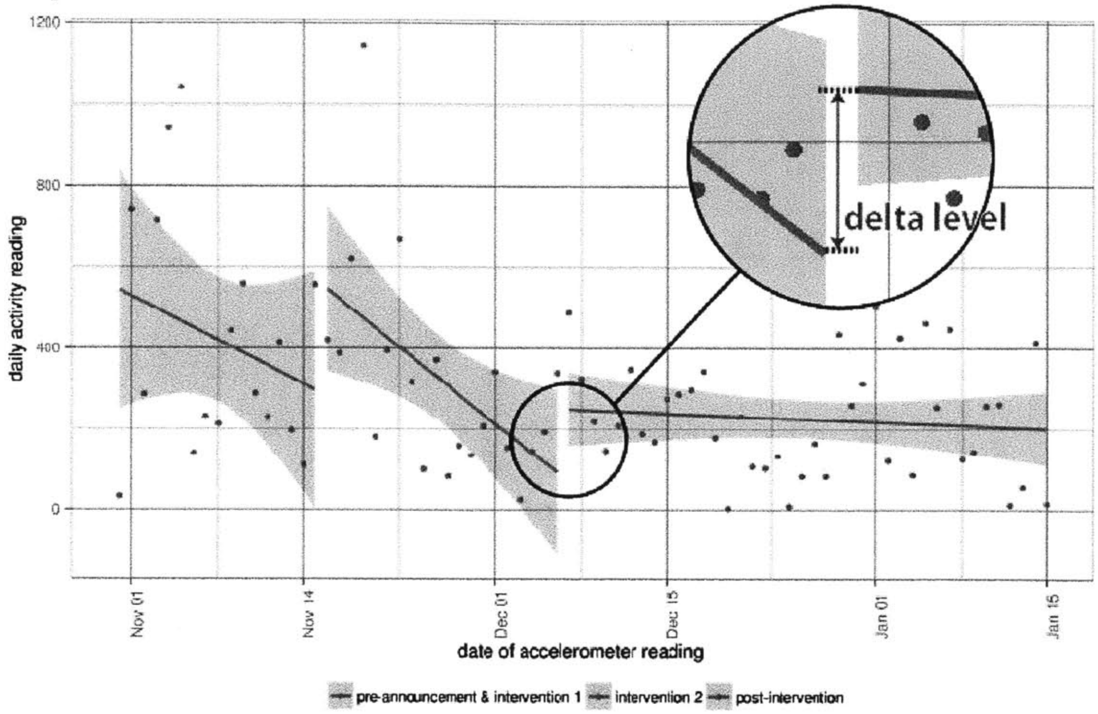
Then, the following measures of behavior change were computed:

1. the change in slope and change in absolute level before and after the intervention was officially announced was calculated: *target_delta_level* and *target_delta_slope.*

2. the change in slope and change in absolute level of linearly smoothed accelerometer readings before and after the intervention was over were calculated: *target_delta_level_sti* and *target_delta_slope_sti.*

The slope and level changes in behavior after the intervention ended will be henceforth referred to as 'stickiness of behavior change' and are very important measures of the success of an intervention in the long term, as explained in the previous chap-

Figure 2-6: Explanation of how slope and level change were computed for each participant



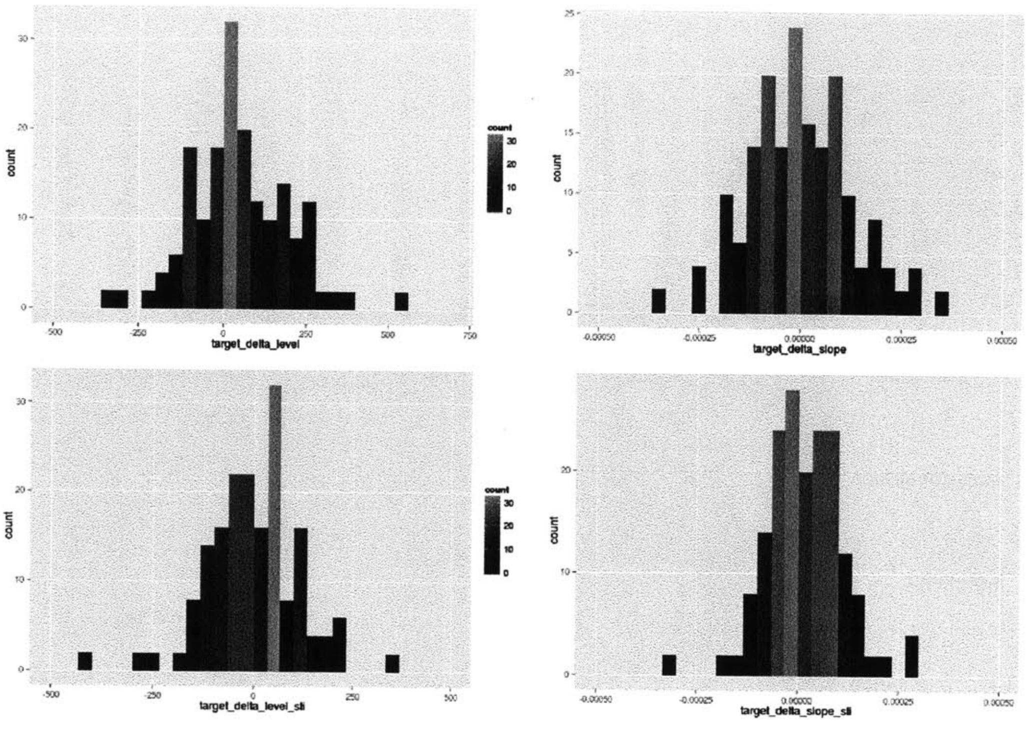
ter. The graphic in figure 2-6 illustrates how the quantities used to measure behavior change were calculated.

After calculating changes in slope and level for each participant, the following the histograms were plotted for all four behavior change measures, as shown in figure 2-7. histogram

2.4 Correlations between interaction and behavior change

Correlation values were found between the behavior change variables (*target_delta_level_sti, target_delta_slope_sti, target_delta_level, target_delta_slope*) and the interaction variables (*friendship, friendship_burt_const, calls_burt_constraint, SMS_burt_constraint, bt_burt_constraint, num_calls, num_SMS, num_bt*).

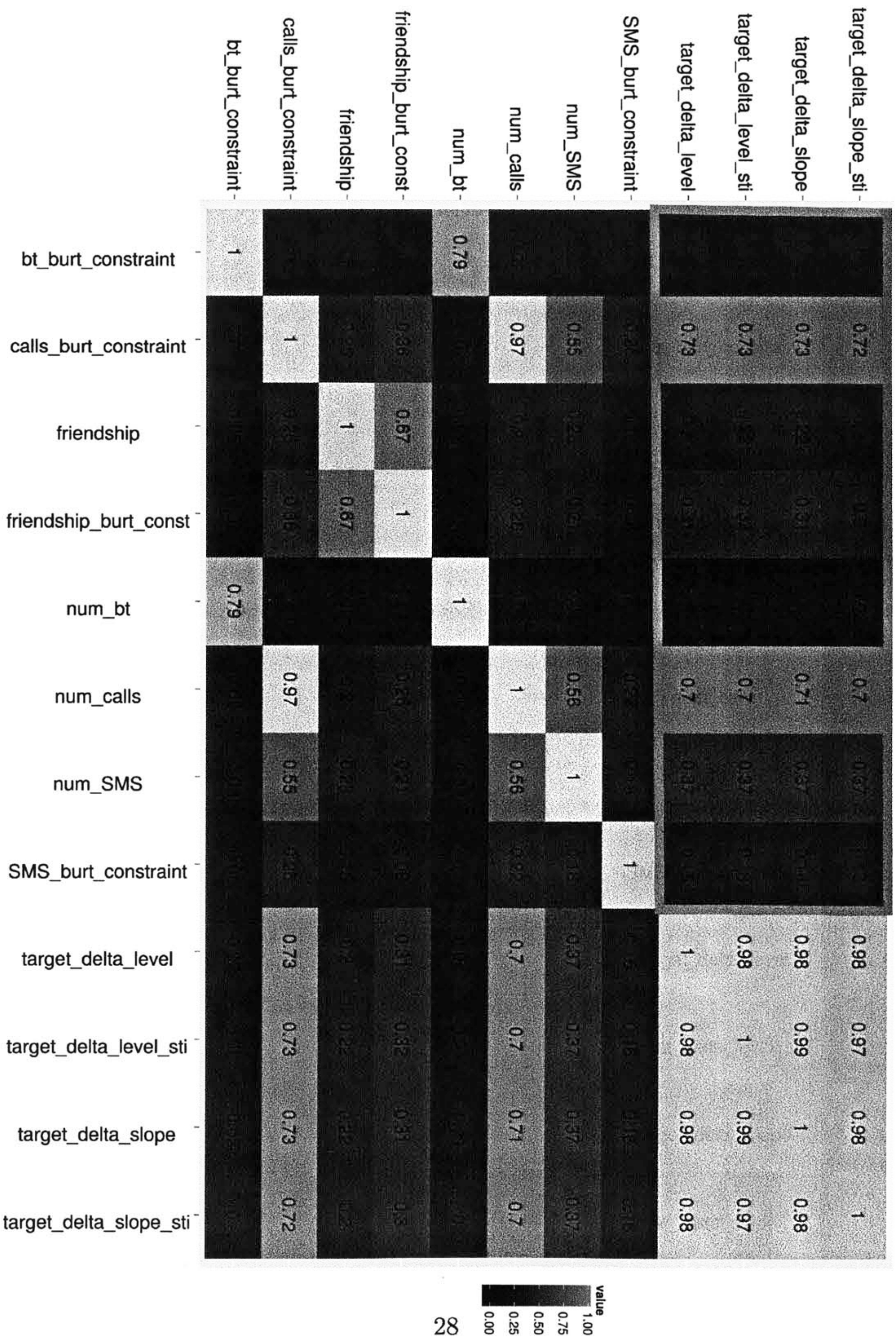
Figure 2-7: Histograms of different slope and level changes during and after the intervention



2.4.1 Pay-peer group

As shown in the correlation matrix heat map below, call interaction as measured by the Burt network constraint, *calls_burt_constraint* (correlation = 0.73), correlates consistently better than the direct call interaction (correlation = 0.7 and 0.71) with behavior change measures. Similarly, Burt network constraint calculated from self-reported friendship, *friendship_burt_const* (correlation = 0.30 and 0.31), correlates consistently better than self-reported friendship (correlation = 0.20 and 0.22) with behavior change measures. Bluetooth interaction as measured by the Burt network constraint, *bt_burt_constraint* (correlation = 0 to -.0.06), exhibits the same amount of correlation as does the direct Bluetooth interaction (correlation = 0.02 to 0.05) with behavior change measures. Conversely, SMS interaction as measured by the Burt network constraint, *SMS_burt_constraint* (correlation = 0.16), correlates consistently worse than the direct SMS interaction (correlation = 0.37) with behavior change measures.

Figure 2-8: Pay-Peer correlation matrix of network interactions and behavior change measures



Several observations can be made from the information above:

1. Bluetooth interaction does not correlate strongly with any behavior change measure. This is unsurprising as Bluetooth logs are gathered passively: as long as one person is within proximity of other Bluetooth broadcasting phones, these phones and hence their owners will be assumed to be interacting. This causes the interaction data to be heavily diluted by a large amount of noise, especially when all participants lived and worked on the same campus.

2. in general, Burt network constraint correlates better than direct interaction. This experimentally verifies our prior hypothesis that accounting for indirect interaction on top of direct interaction is a better predictor of behavior chance and is additional evidence that weak ties contain important information in the network.

3. calls, sms and friendship interaction correlate very strongly with behavior change, calls being the largest.

Therefore, the general observation is that pay-peer behavior is driven by interaction frequency, and the cost of interaction means that increasing frequency provides increasing ability to actively apply social pressure.

2.4.2 See-peer group

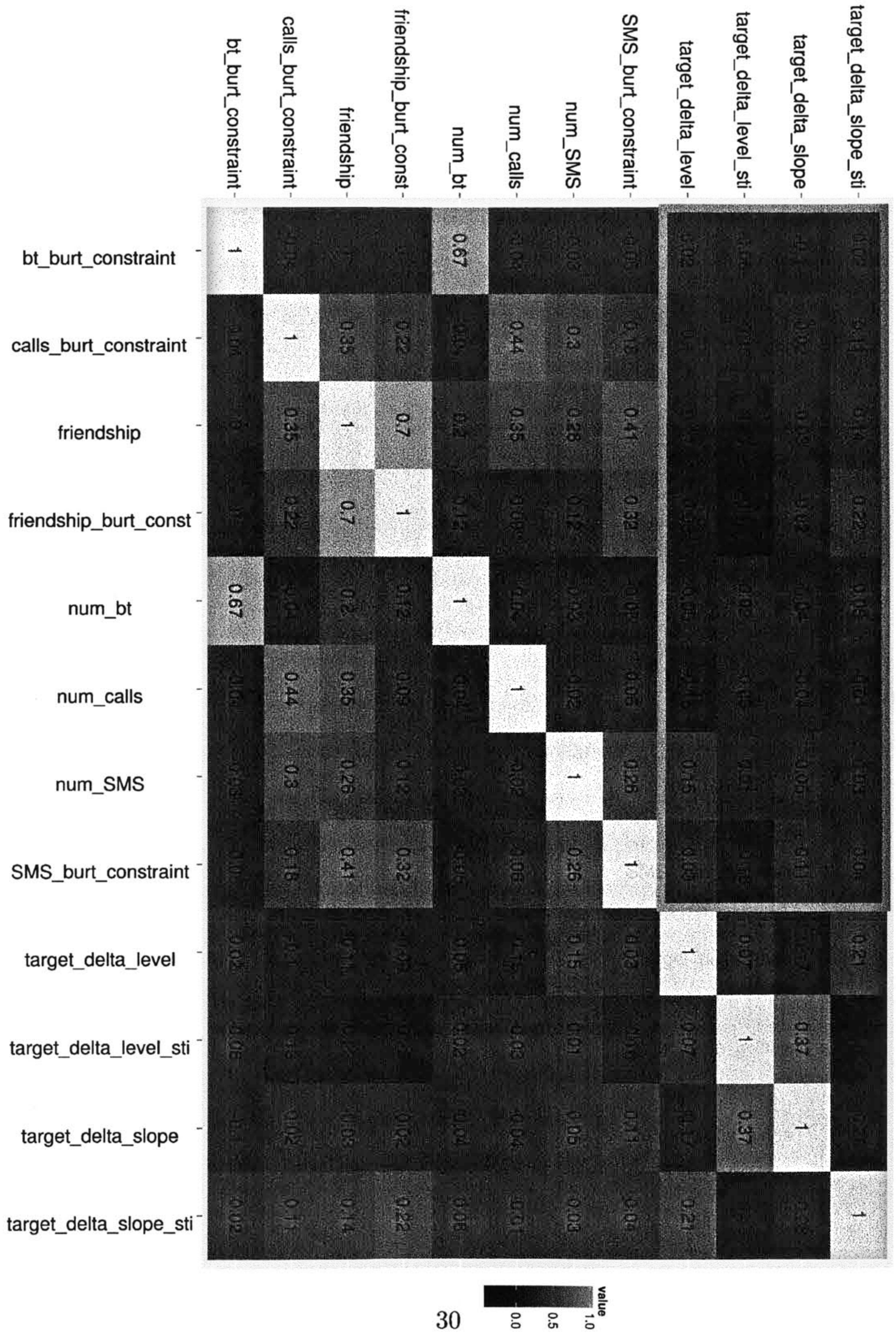
As can be seen from the heat map of interaction metrics and behavior change measures, the correlations for the see-peer group are generally very small, except for self-reported friendship which ranges from -0.25 to 0.22.

This leads to three observations:

1. See-peer, by its very structure, does not harness social interaction as a way to change behavior.

2. See-peer behavior change is more reliant on friendship than on interaction

Figure 2-9: See-Peer correlation matrix of network interactions and behavior change measures



3. Generally, increasing interaction leads to smaller behavior change as per the negative sign of many correlation values.

Further investigation as shown in figure 1-10 below was carried out to see if there is any correlation between interaction and source agent as opposed to target agent behavior change. Again, the same general behavior was observed, except for generally smaller magnitudes of correlation values.

Therefore, as opposed to pay-peer where behavior is driven by interaction, see-peer behavior is driven by friendship relationship where the mechanism to be part of the in-group constitutes a very weak, passive type of peer pressure. This is in accordance to previous work on homophily in groups where

> A pattern as powerful and pervasive as the relationship between association and similarity was underlined and further shows that, As with behaviors, [...] the selection into relationships with similar others appears to be a much more powerful force than interpersonal influence within the friendship network

[12].

2.5 Predictive Model

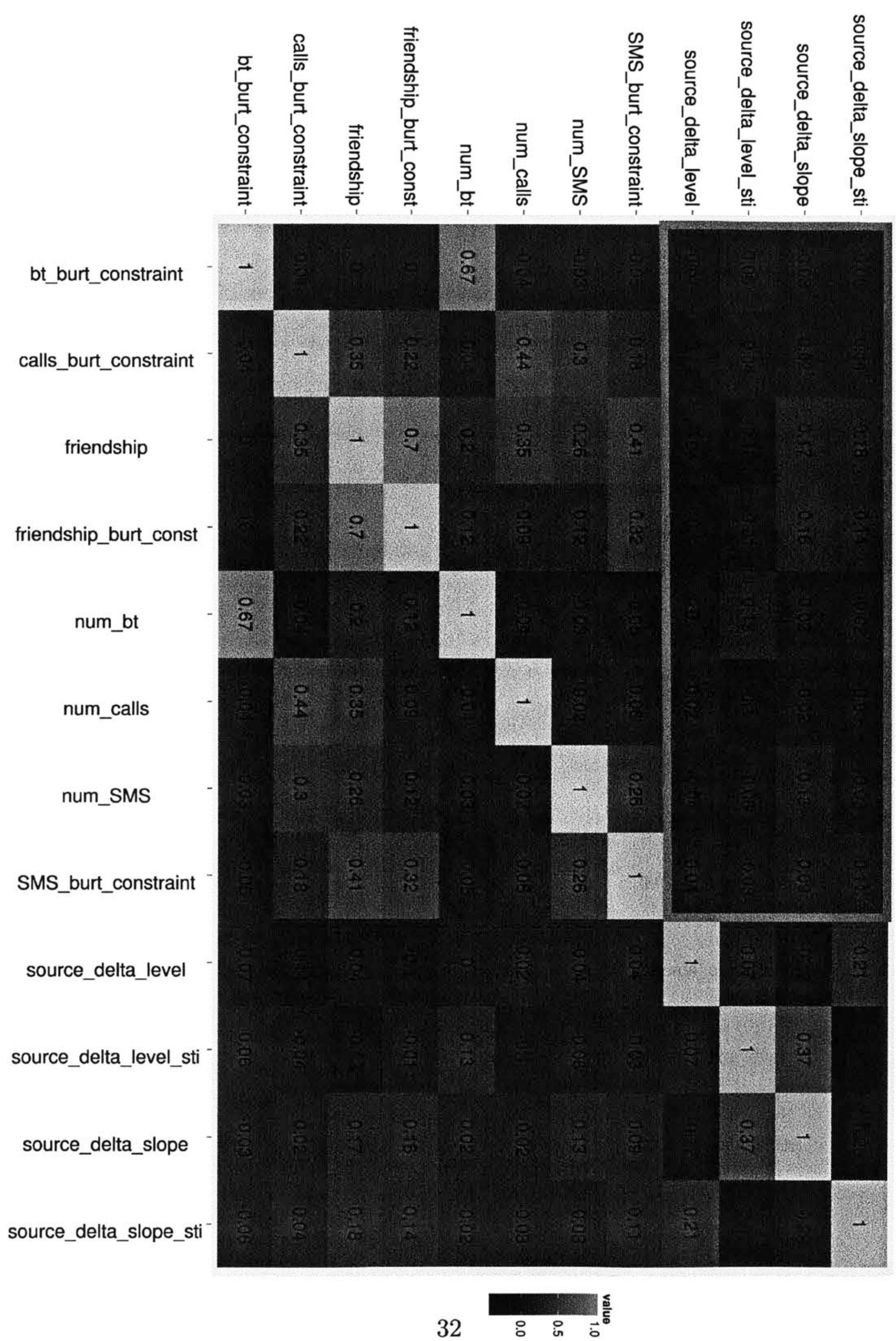
2.5.1 Pay-Peer group

Now that a clear correlation has been established between network interaction and behavior change, a predictive model was built to forecast future behavior of each participant based on past behavior and interaction. Regression models were built for each of target slope change, target level change, target slope change after intervention ended (stickiness), target level change after intervention ended (stickiness).

Since long term accelerometer behavior for each individual is approximated using a linear regression of activity over time,

1. computing the coefficient pair of target_delta_level , target_delta_slope allows the prediction of future behavior during the intervention , and

Figure 2-10: Source agent see-Peer correlation matrix of network interactions and behavior change measures



2. computing the coefficient pair target_delta_level_sti, target_delta_slope_sti allows the prediction of long term future behavior after the intervention was over.

The model was built by regressing each of the four behavior change measures *target_delta_level, target_delta_slope, target_delta_level_sti, target_delta_slope_sti* over the call, SMS and friendship Burt constraints, *calls_burt_constraint + SMS_burt_constraint + friendship_burt_const.* Burt network constraint from calls, SMS and self-reported friendships are the only variables used in the regression because they are the ones with the highest correlations from the correlation matrix discussed previously. Adding direct interaction is not necessary because the Burt network constraint is already a measure of direct and indirect interaction. Similarly, adding other variables such as Bluetooth interaction does not improve the regression, given the very low correlation coefficient (ranging from 0.02 to 0.05) between Bluetooth interaction and behavior change.

A regression for each behavior change measure was run, and the following observations based on Table 2.1 were made:

1. Initially, the R^2 coefficients are around 0.6 but when an outlier was removed, R^2 shoots to approximately 0.9. The same outlier was removed for all the different regressions because the outlier has an unreasonable amount of behavior change value.

2. Within each regression, both call Burt network constraint and friendship Burt network constraint are significant features in the regression whereas SMS Burt network constraint is not significant.

2.5.2 See-Peer group

As discussed previously, the see-peer group offered very few correlations. A regression for the behavior change measures against Burt network constraint of interactions was attempted anyway. As can be seen from the table above, the null hypothesis is not disproven: p-values are too large to show that this is a significant model to predict behavior change from interaction variables.

Table 2.1: Table of regression coefficient data for behavior prediction

	target_delta_level			target_delta_slope			target_delta_level_sti			target_delta_slope_sti		
	p-value	**F-stat**	R^2	**p-value**	**F-stat**	R^2	**p-value**	**F-stat**	R^2	**p-value**	**F-stat**	R^2
overal model	1.17e-40	208.0629443773	0.8801447569	2.26e-43	245.0230129288	0.8963501901	6.12e-43	238.2628486143	0.8937219088	8.83e-37	163.9148311316	0.8526210463
call_burt_const	<2e-16			<2e-16			<2e-16			<2e-16		
SMS_burt_const	0.35726			0.41661			0.58091			0.55289		
friendship_burt_const	0.00324			0.00252			0.00467			0.00277		

Table 2.2: Table of variation before and after intervention

	variation
pay peer friendship change	-0.08268553
pay peer calls change	-0.0681236
see peer friendship change	-0.2275364
see peer calls change	-0.2560559

2.6 Test of interaction and friendship change before and after the intervention

An additional question of interest in this study is to investigate whether such interventions end up changing the pattern of interaction and friendship among participants after the intervention ended. This is important for interventions that are looking to solely change behavior and not the delicate fabric of friendship.

To investigate if friendships and call interaction changed over time, friendship and call interaction for each person before and after the intervention ended were calculated using a regression of calls (or friendship survey values) over time in a manner similar to how accelerometer data was regressed over time. The mean before and after the intervention was calculated for each group, and the difference between these two means was then divided by the standard deviation. A significant deviation from zero of this measure would indicate a change in friendship or interaction. The results can be seen in Table 2.2.

Then a Kolmogorov-Smirnov test was applied to see if there is any significant behavior change in interaction and friendship before and after the intervention. As can be seen from the Table 2.3, no statistically significant change was observed.

2.7 Summary of analysis results

This chapter has attempted to analyze the predictors of success in the technology-driven incentive system. What has been observed so far is that:

Table 2.3: Table of K-S test of variation before and after intervention

	D	p-value
pay peer friendship change	0.1444	0.3048
pay peer calls change	0.1124	0.628
see peer friendship change	0.0889	0.8692
see peer calls change	0.0556	0.9991

1. in the pay-peer group, interaction is a much better predictor of success of behavior change than friendship although both are highly correlated with behavior change

2. in the see-peer group, there is little correlation between interaction and behavior change. However there is non-negligible correlation between friendship and behavior change.

3. A predictive model of high significance was made to predict behavior change for the pay-peer group. A significant such model was not found for the see-peer group.

4. The intervention does not change friendship patterns. However, there is a non-negligible change in interaction pattern in terms of calls.

Chapter 3

Advantages of the technology-driven approach and potential problems

As has been seen from the previous chapter, the technology-driven approach is superior than the traditional non-socially based incentive approach, and the predictors of success of the technology-driven approach have also been investigated.

In addition to producing more behavior change, the technology-driven approach has significant political-economic advantages over the traditional incentive approach. At the same time, although the technology-driven approach is theoretically superior, there are some political-economic pitfalls that should be averted during its implementation. These political-economic advantages and pitfalls will be discussed in this chapter by looking at these three main aspects of the technology-driven approach:

1. how the automated nature of the approach leads to more effective behavior change but can cause market problems,
2. how the fact that the approach harnesses social network pressure makes it more effective but can lead to social problems, and finally
3. how there is indeed a trade-off to be decided between data privacy and effectiveness of the intervention.

3.1 Automated optimization of incentives structures

There are many ways that traditional incentives can be used to increase levels of physical activity such as through taxing electronic sedentary equipment, tax credits for the purchase of health club membership, increasing the gas tax, and parking cash outs (i.e., employees given cash value of parking space) [13]. The success of such policy interventions is unfortunately highly sensitive to the structure of the incentives and the results are very specific to the demographics being intervened on - for example, increasing physical activity might require a completely different incentive structures in groups composed of different ethnicity ratio. The new technology approach does not suffer from these issues of specificity of knowledge because many incentive structures can rapidly be tested live for each new community until an optimum incentive is found. In practice, that would mean putting each subject in the intervention through all the possible permutations of magnitudes and incentive structures over time and looking at which one worked best in terms of achieving the greatest change in behavior per unit dollar. For example, subjects could be paid different amount, or they could be paid for physical performance averaged over different time intervals or they could even be paid based on how much they change their physical activity (the slope of the physical activity curve over time) instead of the absolute value of their final physical activity. Within the machine learning literature, this would mean finding the group of features (slope, absolute value, amount of remuneration, etc.) that produces maximum change in behavior. Another advantage of using such an automated system for devising incentive structures is that it circumvents the need for panels of expert to produce new knowledge about how to change behaviors for every new intervention, as explained in the next section.

Traditionally, to devise a conventional incentive, a group of highly paid experts would have to get together and work towards designing such an incentive. There are many issues associate with this paradigm of design that do not cripple the technology-driven approach. One of the main issues is that the knowledge generated for one intervention (such as for increasing physical activity) might not at all be applicable to another type of intervention (such as smoking) making this highly resource-intensive process non-transferable to other interventions. On the other hand, once the analytics platform is created, the machine learning algorithms will effortlessly search for the most effective incentive structure every time. Another issue is that once the highly traditional resource-intensive design process is over, it is hard to adjust the incentives live while the intervention is still running because it takes so much time and money to get the group of experts to redesign the incentives and because data is so rarely available quickly enough. Finally, a very important issue is that different experts might have different political or academic agendas, or they could be under pressure from industrial and political groups which could derail the process. This is especially true in highly controversial cases such as smoking where there is significant pressure from the tobacco industry not to change human behavior in terms of decreasing smoking habits. Finally, even if it is assumed that impartial knowledge was created during the expert deliberation process, there is always an error bar to each conclusion in science and different experts will consciously or unconsciously attribute different weights to errors based on their own professional and political views on the issue. On the other hand, in the technology-driven approach, the creation of the incentives is created based solely on the optimization of objective measures such as increasing the average physical activity of an individual.

Another advantage of the technology-driven approach is that it minimizes gaming of the system. For example, if an intervention subject finds out what she is being remunerated based on the amount that physical activity changed in a day (the slope) instead of the average physical activity by the end of a day (the absolute value), she could sleep for most of the day until she exercises at the end of the day causing a large change in the amount of physical activity although the average value might be low. Because the system would automatically change the incentive structure every day to optimize objective measures, this decreases chances for gaming the system because intervention subjects will not have time to learn the rules of the system by the time the rules change every day.

There are however many issues with the automated-design of incentives within of the technology-driven approach. A first issue is that some optimized incentive structures might be ethically wrong: for example, the algorithm might find that subjects of some ethnicities need to be paid less than others to change their behavior. If such a technology-driven approach was rolled at national scale, this bias against some ethnicities might be taken as discrimination leading to issues of equity. This can be mitigated by preventing some features such as gender and ethnicity to be part of the incentive structure optimization. However, this would then lead to decreased efficiency as an incentive structure that accounts for variables such as gender and ethnicity would in this case be more effective at increasing physical activity.

Another issue is that longitudinal studies on how different incentive structures drive behavior will not be possible because the structure of the incentives is changing at high rates throughout an intervention and across subjects. Traditionally, a specific incentive structure is tested and then results are analyzed to see how this structure actually improved behavior. Because the technology-driven approach changes the incentive structure continuously, it will be hard to disentangle the effect of how, for example, different specific amounts of incentives changed behavior over a prolonged period of time because these amounts are continuously changed. However, it could be argued that because the design of incentives is automated, there is no need for deeper knowledge of what incentive designs work better as long as an incentives outcome can be measured instantaneously and optimized over time, causing a shift from knowledge-based incentive design to data-driven incentive design.

Even if a good system for increasing levels of physical activity like funf is assumed, there are still potential market failures that can arise from the mere choice of participating in incentive-based interventions whether traditional or technology-driven. For instance, health insurance companies have been increasingly encouraging their members to go to the gym by partially subsidizing their memberships. One problem that can arise in this situation is that of adverse selection: insurance companies will prefer customers who go to the gym because going to the gym is a signal for healthiness which correlates with lower risks and higher long term profits for the company. By providing this healthier segment of their customers benefits and denying less physically active individuals such benefits, they can filter their customers leading to a problem of inequity and the off-loading the higher costs of health care of less physically active individuals to the government system. An argument can be made on one side about how your own choice of lifestyle should impact your future, while on the other side there is a question of equity for those who culturally have not been exposed to the benefits of exercise, or who are physically incapable of physical activity several solutions to this problem will be now be presented.

There are several solutions to the problem of equity. On one hand, the government could step in and ask that everybody participate in such incentive programs so that nobody can be discriminated against. This makes sure that the market signal of participating in the incentive is lost in the noise caused by everybody participating in the incentive program. This does not preclude the issue that the insurance industry can still look at everybodys data and discriminate against unhealthy individual based on their data this issue will be treated in the section on privacy. Another solution could be that legislation would be passed explicitly preventing insurance companies from treating clients that are not part of the incentive program differently. Anybody who has been discriminated against can then sue the insurance company in court this is the torts approach. One problem with relying on courts is that insurance companies and other large organizations have much more resources which they can use to win court cases, while individuals have limited access to information about their rights. Finally, another solution is to hide the identity of incentive program participants from the insurance company by handling the incentive monitoring to a third party organization such as a neutral non-profit organization. Both the government and the insurance industry would benefit from having a healthier population leading to less spending on health care and would thus be incentivize to fund such neutral third-party organizations. Unfortunately, with funding comes influence: the insurance industry or the government could threaten to cut the funding of the neutral third-party organization in exchange for access to their data or in exchange for influencing the design of the incentive system for political and economic advatanges.

Moral hazard is another class of problem with providing incentives for changing human behavior. In the case of increasing physical activity, customers who receive the incentive might partake in unhealthy activity outside the gym such as smoking or over-eating. This will lead to a double cost for the system: more money spent by the insurance company for financing the incentives, and long-term health risks to the individual. Another moral hazard issue is that a subset of customers might not value going to the gym much but will take the offer of the insurance company because of its low costs. This then leads to efficiency costs in the insurance and gym industry by creating an artificial demand for gym memberships and for insurance. Since the individuals data is available to monitor her behavior in the technology-driven approach, if the dimension within which the risky behavior is happening is being measured, then algorithms that include the riskiness of their behavior can easily be incorporated into the reward structure. For example, if the accelerometer shows that the person leads a very sedentary lifestyle outside the gym, this out-of-gym physical activity can be incorporated into the reward structure to make sure the person is encouraged to drive less and walk more, for example. If however the behavior is not recorded such as smoking then the algorithms cannot account for this moral hazard.

3.2 Harnessing the power of the social network

In simple cases such as seat belts, it has been shown that incentives are successful at changing behavior but unsuccessful at achieving long-term change [8] and initiating behavior change [14]. In terms of implementation, there are many channels to providing information to the public - mass media, school programs, and in the age of the Internet, targeted advertisement - that reach individuals on three levels: on the individual level factors such as motivation and knowledge, on the social network level where individuals who have social ties to friends and family members who already have a healthier behavior or who are changing their behavior tend to change their own behavior more, and finally on a community level where a community with strong ties can impose a different norm on an individual [14].

Although there are significant monetary costs to run information campaigns, they generally lead to modest to moderate effects: about 9% of people change behavior for the average campaign, with 17% for campaigns having a legally binding effect to them, and 5% for those without any legally binding requirement [14], in general, campaigns that harness social pressure work better. This is very similar to the significant result of the funf intervention: paying people based on their peer's results produces more change than paying people based on their own activity. What this suggests is that harnessing the pressure from ones social network increases the chance of changing ones behavior: this means that instead of just providing incentives and information to people to change their own behavior, providing incentives that causes peoples friends and family to convince them to change their own behavior works better. Not only does using social network pressure cause greater behavior change, but the closer two people are the more they can influence each other with the interesting result that strangers caused a negative change in behavior: the incentive backfired when trying to use strangers to pressure individuals [2].

Harnessing the social pressure of a network contributes to more behavior change because Individual decision making is not performed in a vacuum. People are embedded in a social-fabric, and social influence has observed effects on personal choice and behavior [2]. Within the funf platform itself, there was no explicit built-in mode of communication for people to influence each other: this was done informally through the daily means of communications between participants such as phone calls of Facebook messages. On the other hand, integrating ways for intervention subjects to communicate with each other on the platform adds to the influence of the individuals social network on her [15] [16].

Although social incentives are very effective at changing human behavior, there are some interesting political and societal issues associated with their effect. First, engaging the whole community into this peer-pressure exercise might damage the social fabric in the long-term. For example, people might decide to interact less after the intervention ends because they get tired of the constant artificial social pressure encouraged by the monetary benefits during the intervention. It might create a dependence on monetary benefits for behavioral change and, finally, it might lead to social fatigue whereby an ever-increasing monetary benefit is required for successful interventions because people can used to a higher amounts of remuneration and social pressure.

On the other hand, the intervention might help to reinforce social ties: people who are closer to each other will start interacting more to pressure each other, while people who are strangers to one another will get to meet and know each other. Hence, not only can the intervention be used to improve physical activity levels in a community [2], but it might also be used as a means to strengthen community ties the latter remains to be tested and is currently the subject of current further analysis. Interestingly, given enough data and analytics, such research on social influence could lead to a general theory of how people influence each other in society and could be very useful in such applications as improving team dynamics in organizations, improving the legislation decision-making process and even finding better matches in the e-dating industry all because knowing how people influence each other can help them live longer and work better together.

A final issue that arises from the fact that this intervention relies on interfering into the social fabric of a community is the question of how much power should the government or companies have in modifying one's social network. A typical individual spends years creating and optimizing her complex social network within a community that could be severely damaged by incentive mechanisms. Some studies suggest that optimizing peoples social network using incentives will help improve productivity [6] but there is always the chance of disrupting the social network enough that the person loses too many connections. In addition to the question of how much can the organization deploying social incentive change ones social network, there is also the question of how much can this organization know not only about the individual, but also the individuals friend. This question is closely connected to the question of how much a company can exploit one's social network for its profit such as through advertising to the individuals contact. Although these are interesting questions, companies such as Facebook and Google already know a lot about our social networks, while ISPs can infer who are our close friends based on our call logs and emails. This leads us to the question of how to balance the effectiveness of social incentives and the notion of privacy which is discussed next.

3.3 Privacy

A significant issue that merits discussion within the technology-driven approach is the problem of privacy: since highly granular data is required to design and compute the incentives, is there any way to do so while still respecting the privacy of the individual and still making a profit from the insurance companys standpoint and still decreasing health care costs from a government standpoint?

The main technical solution to the issue of privacy is through the technique of encryption and the open-source code review of the incentive platform system. Although the data of each user is shared to a central server that computes the incentive rewards for each person, the system can be designed in such a way that the data is still private: only the subject of the intervention and her network contacts would have access to the unencrypted physical activity data. This can be carried out through the use of encryption: the data from each phone can be made to be sent in encrypted form to an encrypted secure server that then does automatic reward calculation sending it back to each subject, again encrypted. The system's code for implementing the encryption can be open for review by the public to make sure that vulnerabilities are identified and corrected. It is important to realize that even though the code is open, the content are still secure because of the way public key encryption works: for example, the code that encrypts all email is publicly viewable whereas the secret key is known only to the user and one cannot decrypt the email even with access to the code implementing the security without the secret key.

Although this technical infrastructure should work from a technical standpoint, there are many important questions to be discussed from a political and social point of view. First, there is the question of who and how will the encryption and open-source code review requirements be mandated? The conventional solution would be to require that the government requires a certain encryption standard and appoints a group of technical vigilantes to supervise the code-review process. There are however limits to this solution: the vigilantes will need to be funded and will end up under the control of those who pay them, whether it is government officials who want to have more access to private information for security reasons or industrial groups who want more data so that they can capture more market share. A more radical and recent approach is to democratize access to the complete code and trust that if the technology-driven approach becomes popular enough, members of the public and academia will report vulnerabilities in the encryption and will report exploitation of the system by the government and industry. This strategy has already proved to be successful from the early days of public computing where disclosure of software vulnerabilities by academics forced companies to update their systems [17].

There are however various problems with this approach. One significant issue is that industry groups could simply refuse to give public access to their incentive platform for intellectual property reasons: keeping ownership of their platform might provide them a competitive edge since software development is costly. Another issue is that industry could require customers who want to buy their insurance plan to give them complete unencrypted access to their data. Fortunately, this would conflict with the Obama administrations views on consumer data privacy whereby Consumers have a right to exercise control over what personal data companies collect from them and how they use it and Consumers have a right to expect that companies will collect, use, and disclose personal data in ways that are consistent with the context in which consumers provide the data [18]. On the other hand, protection of the data from the government itself could be violated because the government might require that weaknesses be created into the system in the form of software doors that allow only the government complete access to unencrypted data should they need to such as in cases of national security. Finally, the implementation of the open-source code review and encryption safeguard solutions could fail because not enough academics and other security and privacy experts might be interested in the incentive platform hence failing to create the active community ecosystem required around the platform to prevent vulnerabilities. For example, it took decades for the Linux system to be adopted by other people than open-source professionals and it takes thousands of volunteers to keep Wikipedia from having knowledge corrupted.

There is no clear solution here: on one end the government could run the incentive platform, pay for the incentives (since it decreases governmental spending on health care in the long run) and control how much industries can use peoples data for profit-making but snoop into people's data undemocratically under claims of national security while, on the other end, if a market driven approach to this problem is taken, companies could each run and fund their own incentive platforms for profit and sell consumers data but might not be able to prevent the government from accessing their clients private data. Conversely, the recourse of academics and consumer groups to sue the government and industry, to outvote the current government, or to boycott certain infringing companies take a lot of time and money and might suffer from the problem of collective action. This very important discussion around privacy is ongoing as there are already companies such as Facebook and Google that have massive amounts of data that they are using for profit-making. Although privacy is very important for this technology-driven approach to be democratic and successful, more discussion about the policy problems imposed by this approach and their corresponding solutions is beyond the scope of this paper.

Chapter 4

Transparency Policies and Citizen Engagement Technologies as a solution

As can be seen from the previous chapter, there are some significant political-economic pitfalls that should be averted during the implementation of the technology-driven approach. Part of the solution the political-economic pitfalls rests on correct technical implementations such as encryption and aggregation. However, in this chapter, I propose novel long-term policy and technological solutions to these problems by relying on more powerful government transparency policies and the encouragement of civically-engaged watchdog technologies.

The rationale behind using transparency policies and civically-engaged technologies is that by giving access to personal data to a powerful organization be it the government or a large company unauthorized use of the data will happen and will be far harder to detect than technical implementation errors. A better long-term strategy is to empower the public so that they can watch over the use of their information. The two overarching ways of doing this are by creating a culture of government transparency both in terms of more transparent functioning of the government and the releasing of more government data and by empowering individuals to create, use and share technology than can be use to watch the watchers.

This, will be the subject of this chapter. I will start with a brief historical description of transparency policies, followed by a more detailed description of ways to delivery transparency, after which I will expose some of the limits of the policy and transparency solutions to avoiding the political-economic pitfalls that should be avoided during the implementation of the technology-driven approach.

4.1 Historical context:

4.1.1 Open-data

In the 1970s, NASA and the general scientific community created a set of technical standards to facilitate access to raw, authoritative, and unprocessed scientific information [19]. These standards would later be known as 'open-data' and, coupled with the ever-expanding reach of the Internet, they would whet the public appetite for data about the public institutions that ruled them. There are now 47 governments that have committed to open government data initiatives around the world, with three of them in Africa: Tanzania, Kenya and South Africa [20].

4.1.2 Open-government

After World War II, the public felt a civic need for greater transparency and accountability [19] probably as a means to increase trust between countries and minimize further conflict. The first major milestone of this civic movement for open government was through the signing of the Freedom of Information Act (FOIA) in 1966 by US President Lyndon Johnson. To this day, FOIA remains one of the foundations of open-data and open-government discourse. Various developing countries looking to open up public data are drafting their own version of the US FOIA: Tanzania is studying best practices in Freedom of Information law to draft its own bill while Kenya is already in the drafting stage. [20].

4.1.3 Secrecy vs openness tension

One of the most fundamental tensions in incorporating more transparency and accountability into the traditional government system is the trade-off between the democratic utility of openness and the security-related need for secrecy. There are many legitimate reasons why a country's government requires a certain amount of secrecy, such as national security and international trade competitiveness. On the other hand, there are many cultural and historical reasons why traditional governments are averse to openness: 1. they value methodical slowness and structural stability [21] instead of being experimental and fast-moving like the private sector 2. they are highly hierarchical and fractured and hence internally competitive instead of distributed and collaborative in the style of open-source Internet projects.

As Roy puts it,

> This defensive mentality and corresponding preference for communications and inward containment of information is part and parcel of the DNA of Westminster governancepolitically and administratively (and how both are intertwined). Here lies the Achilles heel of digital transformationnamely the ingrained resistance of representational democracy and its national institutions to openness and power- sharing and the erosion of public engagement and trust that results

4.1.4 Recent news on openness

On the Obama administration's first day, US President Obama released a Memorandum on Transparency and Open Government committing to 'creating an unprecedented level of openness in government,' and established transparency, participation, and collaboration as the driving principles of the Presidents Open Government Initiative [19]. Soon after, an Open Government Directive followed to guide government agencies on how to implement these requirements for government openness. This directive offered the following main points of guidance [19]:

1. Publish Government Information Online

2. Improve the Quality of Government Information

3. Create and Institutionalize a Culture of Open Government

4. Create an Enabling Policy Framework for Open Government

These two documents were major impetuses to the open data and open government movements in the not only in the US but also internationally, prompting other countries to follow.

4.2 Ways to deliver transparency

Freedom of Information Laws: The aim of Freedom of Information laws is to require a government to release all government-related data unless exempted by the law itself [20]. The first act for requiring access of the public to government records was passed in 1766 and was used to ensure Freedom of Press, suggesting a tight relationship between Freedom of Press and Freedom of Information laws. Freedom of Information laws are the product of pressure from political activism and advocacy groups who want to understand the workings of their government. By allowing citizens to claim their 'right to know', Freedom of Information laws allow the public to witness the inner workings of their political system: they can see the information that the government stores on them and they can access historical records.

In addition to Freedom of Information, specific policies exist to encourage transparency and accountability information to be released for specific domains within the government. There are two types of transparency policies: horizontal and targeted [20]. Targeted Transparency policies exist to further the existing government goals so that the government can regulate specific private and public agencies, e.g. polluters, and mandate them to disclose publicly, factual information, in standardized, disaggregated, comparable formats, concerning specific products. Legally, Targeted Transparency policies are based on existing laws, such as the Emergency Planning and

Right to Know Act. Historically, Targeted Transparency started off as mechanisms for political actors to deal with unpredicted crises. On the other hand, Horizontal Transparency serves to circumvent the government allowing the public to ask for information directly from manufacturers and public service organizations. Their origin can be traced back to the 2004 World Bank report that had concluded that the traditional pipeline delivering information from the government to the public was failing.

4.2.1 Open-Government Data initiatives

As opposed to Freedom of Information laws which provides access to government records, Open-Government Data initiatives try to actively release government data in raw, machine-readable, high-value information in open formats [20]. High-value information can be used to increase agency accountability and responsiveness; improve public knowledge of the agency and its operations; further the core mission of the agency; create economic opportunity; or respond to need and demand as identified through public consultation [20]. Raw data refers to unprocessed, uncensored and non-aggregated data, while machine-readability ensures that the data can be effectively and seamlessly downloaded and processed by members of the public, watchdog organizations and the press. In the words of Vivek Kundra, the Chief Information Officer of the Obama administration, We try to get data as close as possible to the source and in as atomic a form as possible, at the lowest possible level, without violating privacy or security, of course. [22].

In addition to just releasing the data itself, the US government Open-Government Data initiatives are trying to foster communities and tools that enrich the use of the data. Some examples have been Apps for Democracy contests that saved 2.6 millions dollars in developer time in exchange for a $50,000 prize [22] and hackathons to explore the variety and depth of stories the data can tell and to attract new talent outside of the government circles. Many think that Open-Government Data initiatives have been and will continue to be successful avenues for more transparency and accountability because of their deep interaction with several other new innovations:

1. open-source software helped encouraged tool building around democratic data. More and more tools are created everyday that are not only free to use, but are also totally open. Allowing access to the source code of such tools allows programmers to educate themselves from the work of others and contribute back to the tool-building community.

2. Social media allows rapid communication around a variety of subjects. For example, if somebody finds an indication of a breach to democratic values from government data, she can quickly seek the help of the crowd to add the other pieces of the puzzle. This idea of tapping into the consciousness of millions of people has powerful consequences in terms of creating better watchdogs for democracy.

4.2.2 Transparency and Accountability Interventions

As opposed to transparency policies and OGCI where information flows from the government to the public, during Transparency and Accountability Interventions information flows from the public to the state [20]. Transparency and Accountability Interventions happen when members of the public collect, process, visualize and report the information back to the state about specific problems the public is dissatisfied with. They are often driven when people organize socially and then use technology to concentrate information to raise the public awareness about governmental issues such as public finance overspending, failure to deliver government services or inappropriate behaviors of political actors. Examples of technology used include social media platforms such as Twitter, Facebook, and Youtube but also novel tools including mapping technologies such as Ushahidi, Google Maps, etc. In becoming active instruments that broadcast social and political issues, members of the public becoming 'citizen sensors' in that they assess the state of the government. To date, the Transparency and Accountability Initiative has recorded 63 cases of Transparency and Accountability Interventions where members of the public crowdsource the reporting of government issues in low and middle-income countries [20].

Another comparison is that while there is significant scholarly literature on transparency policies and OGCI, there is little scholarly work on Transparency and Accountability Interventions except for very recent grey literature such as reports of the Transparency and Accountability Initiative, a 2012 World Bank report, speeches hosted by the Program on Liberation Technology of Stanford University and working papers [20]. Additionally, Empirically and theoretically grounded research, especially in middle- and low-income countries, is scarce with the exception of Meiers (2011) dissertation, on citizen sensors using the Ushahidi platform for political mobilization in Egypt and Sudan [20].

Although Transparency and Accountability Interventions are very potent means for the public to report failures of the governemnt, there are criteria to be respected for the information to count as legitimate. For instance, the geographic data gathered by members of the public must pass scientific standards of quality test. Similarly, for crowdsourced reports to go beyond being scattered anecdotal pieces of information, they have to be legitimated by official government data. For example, anecdotal reports of government misuse of money have higher chances of receiving corrective actions if they are corroborated by budget numbers. On the other hand, significant variations between official numbers and actual citizen reports can also lead to corrective measures.

4.2.3 Citizen apps

Freedom of Information laws and Open-Government Data initiatives lead to the release of a lot of government information. On the other hand, Transparency and Accountability Interventions seek to use government data to report on government failures. Citizen apps can serve as a bridge between between these two mechanisms for Transparency and Accountability by harvesting the power of government data for positive change. Citizen apps come in many forms, at many scale and attempt to solve many different types of problems. Unlike the policy, official initiatives and intervention approaches, citizen apps are fundamentally always evolving and follow more of a market-approach: many people make many of them and the one] that go viral are the ones that stay.

Citizen apps use two main types of data. Often, they will use government data from official sources where their main tasks is to aggregate and present the data in digestible up-to-date forms to the public. These apps are mostly passive in that they rarely allow direct feedback to the government. Some examples are websites (web apps) that collects government data such as budget amounts and allows the public to visualize and search the data in a useful way one such example is opensecrets.org.

On the other hand, there exists civic apps which harness user-generated data and they range in levels of active participation required by the public. The most passive apps are commonly used just to express opinions or call for awareness: examples are Twitter tweets or Facebook posts in which users share issues they are concerned about. Sometimes, the issues go viral they are shared by large numbers of people and prompt public outrage which then requires government action. A poignant example is the case of a the Facebook page "We Are All Khaled Said that is believed to have initiated the Jasmine Revolution that eventually caused the overthrowing of several governments in the Middle East. At the other extreme of the spectrum of active involvement required are civic apps such as Ushahidi whose data come exclusively from people actively sending messages whether as SMS, email, videos, etc to the platform with the intent of improving the situation on the ground.

Irrespective of where citizen apps get their data, there are four goals that this mechanism for Transparency and Accountability aims for [20]:

1. Opinion seeking: these apps serve as forums where people ask and answer questions about various issues. They are used as information gateways to match professionals with people needing help. They can range from being very informal such as Reddit and Facebook where people can post questions on very different matters to being very formal such as German websites Abgeordnetenwatch.de (Parliament Watch), kandidatenwatch.de (Candidate Watch) and Mehr Demokratie e.V. (More Democracy) where people can ask questions directly to political actors.

2. Problem identification: these civic apps aim at allowing the public to report problems they individually find, and also to allow individuals to check if there are others who have been victim of the same problem. One of the most recent example is fixmystreet.com which allows residents of certain areas to report road potholes, to the corresponding public services and to check if other people have also reported these issues. These applications are very helpful because they allow rapid communication of problems to the government, rally people with similar issues, and prevent duplication of work from the side of the government.

3. Problem resolution: there are three approaches to using civic apps for problem resolution. The first way is to use apps to get people to help each other find answers to questions. Some examples are web systems such as politics.stackexchange.com where people can ask questions they have about the law and point out issues they have seen with political decisions. Another approach is using the civic apps as a means to relay the information about citizen problems to the government who then steps in to evaluate and resolve the issues. An example is change.org where people can create petitions that can be used to pressure the government to add certain issues to its agenda note that the pressure is exerted by informal means because it helps the government realize that suddenly there are millions of people who signed a petition about a certain issue. Finally, there are civic apps that pressure the government directly. One example is the White House Petition system which allows individuals to asks the White House to add items to its agenda: if a certain number of people sign the petition, then the White House automatically adds reviews the item and issues a response.

4. Creating awareness: Civic apps can be also be used to raise awareness of specific issues. Since links to civic web apps can be shared easily, civic apps can be very helpful in virally reaching millions of people. Recent examples include the use of Twitter and Youtube to raise awareness about the serious abuses happening in the Middle East which eventually led to the Jasmine Revolution and the activism of Reddit, Google and Wikipedia in raising awareness about

the democratic and technological issues associated with the recent SOPA and PIPA bills.

4.3 Limits

There are some limitations with using open-data and open-government as mechanisms to promote Transparency and Accountability.

One of the main issues with open-data and open-government is that they are sometimes used as an easy way for a government to appear transparent. A fundamental problem is when the government willingly or unwillingly confuses the adoption of open-data standards for the deeper longer term process of modifying the very functioning of the government system to be more transparent. One example is if a government keeps the decision-making process of public policy enshrined in secrecy or keeps the donations of lobbies to political actors private but still credits itself for transparency by releasing irrelevant information about policy-makers: open data [provides] an easy way out for some governments to avoid the much harder, and likely more transformative, open government reforms that should probably be higher up on their lists [19]. Another problem is that the data released could be released in obfuscated formats that cannot be easily used for reporting failures of governance and service delivery. In the long term, this confusion could lead to frustration of the public or worse, slow down the open-data and open-government movements.

Even if a government wants to implement effective transparency and accountability mechanisms using technology, the implementation can sometimes be too optimistic. One possible problem is that government assume that if they release their data, people will automatically start using it. Instead, one strategy that has proved to be more successful is to build an ecosystem of enthusiastic hackers and companies around the data such as through competitions, hackathons, prizes and internships [22]. Another problem is that the website broadcasting data has to be very intuitively and intelligently designed so that a maximum number of people can quickly learn how to use it. Similarly, the public should be educated about the potential benefits of how to use the data productively and critically such as through civic classes in school and public campaigns. Finally, the government should work closely with the media to make sure journalists can give feedback to the government on what kind of data they find useful. Unfortunately, since the open data and open government movement is at its infancy, there are not always established best practices on how to design good open data gateways.

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