Communication Patterns and Performance in Early Startups*

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Abstract. We use electronics badges to measure in-person communication across companies from an accelerator program, and analyze its relationship with their performance. Our analysis shows that both subjective and objective performance correlates with the amount communication exhibited by early stage companies. In general, more communication correlates with better performance, though too much communication with other teams seems harmful. Lower internal communication entropy correlates with higher performance. Companies that spent more time with the program mentors do better. Large companies reported higher levels of satisfaction compared to small companies.

Keywords: Startups · Accelerators · Group dynamics · Social networks · Wearable sensors

1 Introduction

The ability to predict the success or failure of an early stage company is critical for accelerator programs and investors. Prior studies marked human and social capital as important factors determining the potential of a startup to succeed [9, 1, 3]. However, very little is known about the effect that founders' interpersonal relationships have on the success of their companies, and the effect of their relationships with other startups located in the same innovation space on their performance.

To investigate these relationships, we use Rhythm Badges [12], a wearable sensing platform to measure social interaction in a longitudinal study in a university startup accelerator program. We find that higher internal communication correlate with better, more consistent, performance. Lower internal communication entropy correlate with higher performance, suggesting that companies with central leadership do better. Communication with other teams favors moderation, and companies that spent more time with mentors do better. We also show that small companies reported lower performance.

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2 Related Work

According to the literature, patterns of communication are an important predictor of team performance. Researchers have found that a higher volume and frequency of interaction facilitated better coordination and correlated positively with high performance [18]. Wooley et al. [23] showed that the distribution of participation was highly predictive of team performance in laboratory tasks—the more evenly team members communicated with each other, the better the team performed. Finally, researchers have found that co-located team members could passively observe each other, learning about the project's progress and what others are doing [22, 10, 17]. These results need to be validated in early venture teams because of the complexity, uncertainty and ambiguity of their work.

Just as the interactions within a team are important to its success, so are the interactions with other teams. Modern teams do not work in a vacuum, but instead depend on a complex network of formal and informal social ties to other teams in their organization [2, 14]. These ties and the network structure they create can improve information flow, bringing in new knowledge, opinions, and ideas to the teams [18, 21].

Similarly, the relationships between the startup and other co-located companies may have an effect on performance as well. A common claim made by startup accelerators, incubators, and co-working spaces is that these environments promote creativity and innovation by facilitating the exchange of ideas and knowledge [5, 15, 7]. To the best of our knowledge, this presents the first attempt to validate these claims.

Researchers [18, 23, 16, 4, 6] have used wearable devices to measure face-to-face time and vocal activity in field studies, in order to reveal the internal structure and communication patterns of teams. Hung and Gatica-Perez recorded audio and visual signals from small-group meetings in order to measure cohesion levels [8]. The automatic measurement of these signals using sensors allows for measurement of social interaction in a scalable, objective, and cost-effective manner [19].

The open source Rhythm Badge, part of the Rhythm platform [12, 11], further advances the state of the art. It has a longer battery life and a smaller form factor as compared to the Sociometric Badge, and its minimalist design makes it much more affordable to make. The Rhythm Badge enables the automatic measurement of social interaction in a form factor similar to employee name tags, making it more socially acceptable to wear and easier to use.

3 Data

To study the relationship between interaction and performance, we recruited early stage startup companies from a university startup accelerator program located in Cambridge, Massachusetts. This program offers guidance and mentoring to student-led startups for a period of three months during the summer. The program provides monthly stipends to students, and awards up to $20K equity-free additional funding for the venture, based on the company progress.

We recruited 19 of the 20 companies in the Cambridge location, with a total of 82 participants. We also recruited seven mentors and nine staff members to take part in the experiment. Two companies were not included in the analysis due to compliance issues. The remaining 17 companies included a total of 67 members, with an average company size of four.

We instrumented the participants with Rhythm Badges to quantify face-to-face communication and conversational patterns, and asked them to answer a daily survey with two questions:

Q1, Project Progress: How confident do you feel about the progress of your project in the past 24 hours? (7-point Likert scale)

Q2, Teamwork Quality: To what extent do you agree or disagree with the following statement: My team worked well together in the past 24 hours. (7-point Likert scale)

4 Methods

4.1 Subjective performance

We used the daily survey data to create two resolutions of performance measures for each question—daily performance, and overall performance. Daily performance is the average response of all members of company for a given day,

$$q\_daily\_mean_{c,t} = \frac{\sum_{i \in c} q_{i,t}}{r_{c,t}} \tag{1}$$

and the overall performance is the average response of all company members for the entire duration of the experiment:

$$q\_overall\_mean_{c} = \frac{\sum_{i \in c, t \in T} q_{i,t}}{r_{c}} \tag{2}$$

where c is the company, t is the day, i is a company member and r is the number of responses.

We also calculate the variance for each day as a way to measure the similarity in company members' responses for a given day, $q\_daily\_var_c$, and the variance in all responses for a given company, $q\_overall\_var_c$.

4.2 Objective performance

The third performance measure we used was milestone rewards, which is based on the progress that companies made every month. The more milestones the company reached, the more funding it received from the accelerator. We annotate this performance measure as $milestone\_rewards_c$.

4.3 Measuring Communication

We used the proximity data collected by the badges to determine the amount of communication between participants. Each company was assigned to a number of tables in two large open spaces in the accelerator program, based on its size. Because of the density of the space, we could not distinguish between actual face-to-face interaction and people sitting close to each other. We therefore decided to use a threshold that captures all interaction within several feet.

We defined $minutes_{ij,t}$ as the number of minutes the pair i, j spent in close proximity on date t. Next, we counted the number of minutes of communication within the company, $minutes\_company_{c,t} = \sum_{i,j \in c} minutes_{ij,t}$ and with participants of other companies, $minutes\_other_{c,t} = \sum_{i \in c, j \notin c} minutes_{ij,t}$. We then normalized the number of minutes using the company size.

To calculate the communication entropy, we first calculate Shannon entropy:

$$H_c = -\sum_{i=1}^{k} p_{c,i} log(p_{c,i}) \tag{3}$$

where k is the company size, and $p_{c,i}$ the proportion of company c total minutes of interaction involving member i. We then define communication entropy as the Shannon entropy normalized by k:

$$minutes\_company\_entropy_c = \frac{H_c}{log(k)} \tag{4}$$

4.4 Analytical Approach

We calculate terciles based on the amount of communication and determine three levels—small, medium, high. We then use the Mann-Whitney U test [13] to compare performance for different levels of communication. A similar approach was used for comparing the performance of companies of different sizes.

The Mann-Whitney U test was chosen over the two-sample t-test [20] because the latter assumes normal distribution. Using the one-sample Kolmogorov-Smirnov test, we tested for normality of the data distribution, finding the distribution not to be normal.

5 Results

5.1 Within-team communication

Figure 1a shows the objective performance, based on milestone rewards, for different levels of communication within the teams. Comparing low to medium and high levels of communication reveals that the amount of conversation positively correlates with objective performance ($p < 0.05$). A similar analysis for the entropy of the time members spend with their team shows that companies with

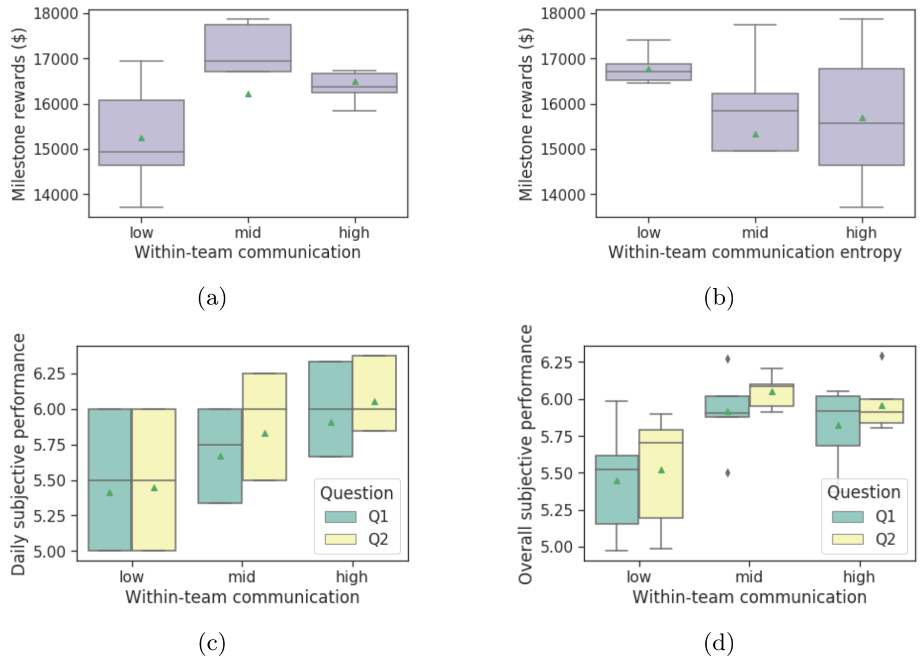


Fig. 1: Comparison of performance for different levels of within-team communication. Panel (a) shows the objective performance of startup companies (money awarded based on milestones achieved) as a function of within-team communication. Panel (b) shows the objective performance as a function of within-team communication entropy. Panel (c) shows the daily subjective performance (based on self-reported measures) as a function of within-team communication, colored by the performance measure – Q1 measures reported project progress and Q2 measures reported teamwork quality). Panel (d) shows the overall subjective performance as a function of within-team communication. Communication measures are normalized by company size. Levels represent terciles. In the boxplots, the triangle indicates the mean, the horizontal line that divides the box into two parts indicates the median, and the dots indicate outliers.

low communication entropy do better on the objective performance measure ($p < 0.1$, Figure 1b).

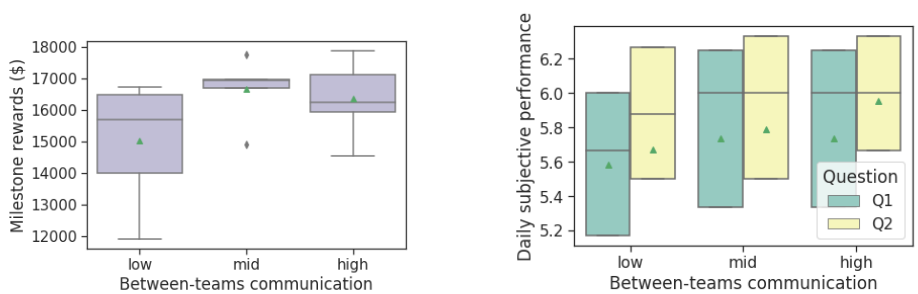
The subjective performance measures show similar results. Comparing low to high levels of communication reveals that for both questions, the amount of conversation positively correlates with daily subjective performance ($p < 0.01$, Figure 1c), as well as with the overall subjective performance ($p < 0.05$, Figure 1d).

Similarly, we find that the performance variance decreases as interaction increases, suggesting that people form similar opinions on the project progress (Q1) and teamwork quality (Q2) when they spend more time together, or that the performance for highly interactive teams is more consistent. These results are significant both in daily and in overall resolution ($p < 0.05$), except for the project progress question (Q1) in daily resolution ($p > 0.1$).

5.2 Between-team communication

Figure 2a shows the objective performance, based on milestone rewards, for different levels of communication with other teams. Comparing medium to low and high levels of communication shows that companies with a moderate amount of communication with other teams did better ($p < 0.1$). This suggests that having too much or too little interaction with other companies may be harmful.

The subjective daily performance of the companies shows a slightly different result. Comparing low to high levels of communication reveals that for both questions, the amount of conversation with other teams positively correlates with subjective performance ($p < 0.1$, Figure 2b). This suggests that days with more between-team conversation tended to be days that were judged better by the participants. We also find that the performance variance decreases as interaction increases ($p < 0.01$), suggesting that participants formed similar opinions on the project progress (Q1) and teamwork quality (Q2) when they communicated more with people outside their company.



(a) (b)

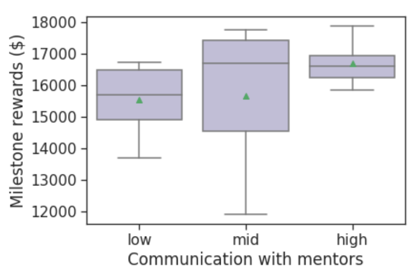
Fig. 2: Comparison of performance for different levels of between-team communication. Panel (a) shows the objective performance of startup companies (money awarded based on milestones achieved) as a function of between-team communication. Panel (b) shows the daily subjective performance (based on self-reported measures) as a function of between-team communication, colored by the performance measure – Q1 measures reported project progress and Q2 measures reported teamwork quality). Communication measures are normalized by company size. Levels represent terciles. In the boxplots, the triangle indicates the mean, the horizontal line that divides the box into two parts indicates the median, and the dots indicate outliers.

5.3 Communication with mentors

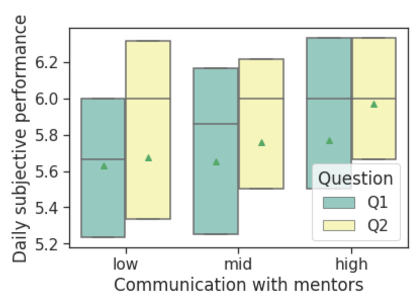
Figure 3a shows the objective performance, based on milestone rewards, for different levels of communication with mentors. Comparing low to high levels of communication with mentors shows that companies with a large amount of communication did better ($p < 0.1$).

The daily subjective performance measures show similar results. Comparing low to high levels of communication reveals that for both questions, the amount of conversation with mentors positively correlates with subjective performance ($p < 0.05$, Figure 3b). This suggests that days in which the teams communicated with mentors tended to be days that were judged better by the participants.

We also find that the variance of daily performance decreases as interaction increases ($p < 0.05$), suggesting that participants formed similar opinions on the project progress (Q1) and teamwork quality (Q2) when they communicated more with the mentors.



(a)

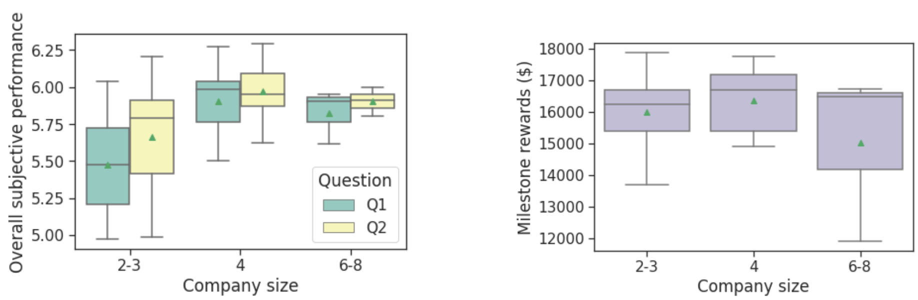


(b)

Fig. 3: Comparison of performance for different levels of communication with mentors. Panel (a) shows the objective performance of startup companies (money awarded based on milestones achieved) as a function of the communication with mentors. Panel (b) shows the daily subjective performance (based on self-reported measures) as a function of the communication with mentors, colored by the performance measure – Q1 measures reported project progress and Q2 measures reported teamwork quality). Communication measures are normalized by company size. Levels represent terciles. In the boxplots, the triangle indicates the mean, the horizontal line that divides the box into two parts indicates the median, and the dots indicate outliers.

5.4 Company size

Figure 4a shows overall subjective performance for different company sizes. Comparing small to medium and large company sizes reveals that for both questions, the company size positively correlates with subjective performance ($p < 0.1$). This suggests that larger companies were judged better by the participants themselves. The objective performance, however, does not show a significant difference for companies of difference sizes (Figure 4b)



(a) (b)

Fig. 4: Comparison of performance for different company sizes. Panel (a) shows the overall subjective performance (based on self-reported measures) as a function of company size, colored by the performance measure – Q1 measures reported project progress and Q2 measures reported teamwork quality). Panel (b) shows the objective performance of startup companies (money awarded based on milestones achieved) as a function of company size. Levels represent terciles. In the boxplots, the triangle indicates the mean and the horizontal line that divides the box into two parts indicates the median.

6 Discussion & Conclusion

We used a combination of wearable devices and surveys to measure the relationship between communication patterns and the performance of startups in a university accelerator program. Our results show that companies with higher internal communication exhibited better, more consistent, performance. Lower internal communication entropy correlated with higher performance, suggesting that companies with central leadership do better. External communication seems to favor moderation for overall performance, and days with more interaction with other companies were judged better by the participants. Companies that spent more time with the program mentors are the ones that did better. We also show that medium and large companies reported better performance, compared to small companies.

These results confirm some of the best practices used by accelerator programs. They show the value of providing companies with a physical space in which team members can spend time in-person as well as communicate with peers from other companies and with mentors. The results also support accelerators and investors preference for working with larger teams.

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