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BOARD #154: Work in progress: Examining the network growth strategies of early-stage entrepreneurs

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Work in progress: Examining the network growth strategies of early-stage entrepreneurs

Abstract

Research in innovation management and entrepreneurship highlights that an individual's network can impact entrepreneurial success. Personal networks help individuals identify entrepreneurial opportunities, find diverse ideas and relevant information, and access entrepreneurial support resources. This study examines the impact of individual and programmatic factors on network growth and corresponding impact on entrepreneurial success. The study follows the network evolution of participants in NSF I-Corps, an entrepreneurial training program for early-stage deep technology entrepreneurs. Participant ego networks were captured by having participants enter anonymized data (all people are numbers) on connections from the online platform LinkedIn. Additional data on strength of connections was also captured for each connection. Participants were also asked to identify which connections were gained through the training program. Participant networks were analyzed to determine underlying network structure. This involved the use of network structural metrics such as centralization, density, and proportions of strong ties. Analysis of network structural metrics over time was used to quantitatively represent different networking strategies. Differences in participants' networks across different cohorts and sub-programs within the training program will be used to identify best practices for improving innovation and entrepreneurial outcomes.

Introduction

Successful entrepreneurs start and manage a growing business in an original direction, also known as a venture, at a profit. Entrepreneurial success has been repeatedly tied to economic growth [1] and positive social change [2]. As entrepreneurs often take significant financial risks to get started and their success can benefit so many, understanding how to support their success as much as possible is critical. An entrepreneur's ability to build and sustain their network is an important element of their success, as networking ability has been shown to positively affect the financial performance of new ventures [3] and the ability to attract larger institutional investors [4]. This connection has been found to be the most pronounced for younger ventures [3]. Certain networking strategies, such as consciously developing non-redundant relationships, or ties, over time, helps entrepreneurs obtain investments from these more impactful institutional investors [4]. Quantitative descriptors of networks, such as network size, position, centrality, and weak ties, have been studied in the context of entrepreneurial networks [5, 6]. A start-up's position in the global start-up network, specifically how well connected it is (known as centrality), was found to be a predictor of future success [7]. Other network measures, such as the level of weak ties or relationships, have also been found to be associated with entrepreneurial innovation and success [6], though some studies have suggested that the benefits are dependent on an individual's position within the network or the radicalness of the innovation [8, 9].

Understanding if an entrepreneur's network is indicative of success depends on obtaining their network data. Traditional techniques use surveys and interviews but can capture only a subset of an individual's professional ties. This makes it challenging to form a comprehensive view of an individual's network, particularly important when studying the effects of structural constructs [6]. Digital platforms like LinkedIn are popular as they allow entrepreneurs to effectively manage and grow their networks, presenting an opportunity to study entrepreneurial networks at a larger and more complete scale. Active use of professional social networking sites has been found to be linked to informational benefits for users [10, 11], with network composition being an important variable in accessing these informational benefits [10].

LinkedIn data, which captures the date connections were made, can be used to map network evolution over time. This paper examines the LinkedIn networks of participants in the National Science Foundation's Innovation Corps (I-Corps) program, an entrepreneurial training program for deep technology researchers. I-Corps is an experiential, entrepreneurial training program that supports academic researchers and engineers in translating technologies from research to market implementation. A key component of the program is customer discovery, an immersive process during which participants interview stakeholders to refine their business model. This study explores how participation in I-Corps influences the network structure of participants and their success, examining differences across regional and national programs.

Methods

Data Collection

Data was collected from 7 participants in the NSF I-Corps program at both regional and national levels. This study was approved by the institutional review board (IRB) at Texas A&M University (IRB Study ID: STUDY2023-0096). Participants were recruited via email from NSF I-Corps cohorts and all participants provided written informed consent prior to participating in the research.

Details of participants' personal networks were captured through one-on-one interviews or a self-guided data conversion process, depending on participant preference. The procedures were designed to ensure confidentiality for participant connections. The data conversion process determined how a participant's connections are connected to each other, creating the network structure. Collected data included connections' company type, position type, common connections with the primary participant, and when the connection was made. A website developed by the research team helped the participant replace names with numerical identifiers. Participants were also asked to record how close they were to each connection, rating them based on how comfortable they were reaching out for professional advice (scale of 1 to 7, with 1 being a weak tie and 7 being a strong tie). Participant contacts who were not connected with them on LinkedIn were not considered for this study.

Participants also shared de-identified information about the individuals that they interviewed during the I-Corps program using a template created by the research team. This data was linked to the participant network data captured from the interviews. Participants were also asked to share a copy of their I-Corps team presentation at the end of the program.

Surveys provided additional contextual information, including entrepreneurial impact, technology transition success, and participant demographics. The surveys were administered at the beginning of the program and end of the program. Future work will incorporate longitudinal surveys administered 12-months after the program.

Data Analysis

Graphs were created to visualize the participants' networks (see Figure 3 in the Results section). Connections were recorded as undirected links (or edges), without a specific direction noted, and people - including the participant (or the ego) - were represented as nodes. Connection data was recorded as an edge list and was used to calculate network density and centralization. Network density, known as linkage density in ecology, is the number of edges divided by the total number of possible edges (Eq. 1, where N is the total number of nodes and L is the actual number of edges) [12]. Centralization is a network level measure referring to the extent to which a network is dominated by a single node. Centralization here is calculated using node-level degree centrality (Eq. 2), which determines the importance of a node (N_i) based on how many ties it has to other nodes (L_{Ni}). Centralization (Eq. 3) is then the sum of the differences of each node's centrality and the centrality of the most central node, normalized by the maximum possible sum of differences (calculated for a star graph, or a graph with one node connected to all other nodes, of the same size) [12]. Density and centralization are calculated omitting the ego node ($i=0$).

$$density = \frac{L}{N(N-1)/2} \tag{1}$$

$$node\ degree\ centrality\ (N_i) = L_{N_i} \tag{2}$$

$$centralization = \frac{\sum_{i=1}^{N}\left(L_{N_i,max} - L_{N_i}\right)}{\sum_{i=1}^{N}\left(L_{N_{star},max} - L_{N_{star},min}\right)} \tag{3}$$

A subgraph of the participant network was generated for each available time point to map the evolution of network structure over time. The date associated with the first connection that a participant made was considered time point 1. Network metrics such as network size (N), density, and centralization were evaluated for each subgraph.

The network growth rate (Eq. 4) for an interval was calculated as the change in network size (N) during that interval divided by the length of the interval (t) in days. Network growth rates were calculated for three different time intervals – two months before the start of the program, during the program, and two months after the end of the program. Density and centralization gradients were similarly calculated as an average rate of change over fixed intervals.

$$dN/_{dt} = \frac{N(t_2) - N(t_1)}{t_2 - t_1} \tag{4}$$

Results and Discussion

Figure 1 illustrates the variation in network density (top) and network centralization (bottom) for seven participants at three time points – just before the start of I-Corps, just after the end of I-Corps, and two months after the end of I-Corps. Three participants' data were omitted as one was an industry mentor in the I-Corps program and not an entrepreneurial lead, and two others were missing connections data before or after the program. Density is a measure of the interconnectedness in an individual's network, and a higher density implies a lower likelihood of new resources or heterogeneous resources being available within the network. The program, both regional and national, caused all the participants' networks to become less dense and indicates access to a wider range of opportunities. Network centralization can indicate if there are certain nodes that control access to resources such as information, advice, or other intangible resources within the network. Higher centralization would suggest that the participant has fewer opportunities to access resources in the network. A more centralized network might also offer lower diversity of resources. The decrease in network centralization after participation in I-Corps seen in Figure 1 is a positive sign of increased network diversity.

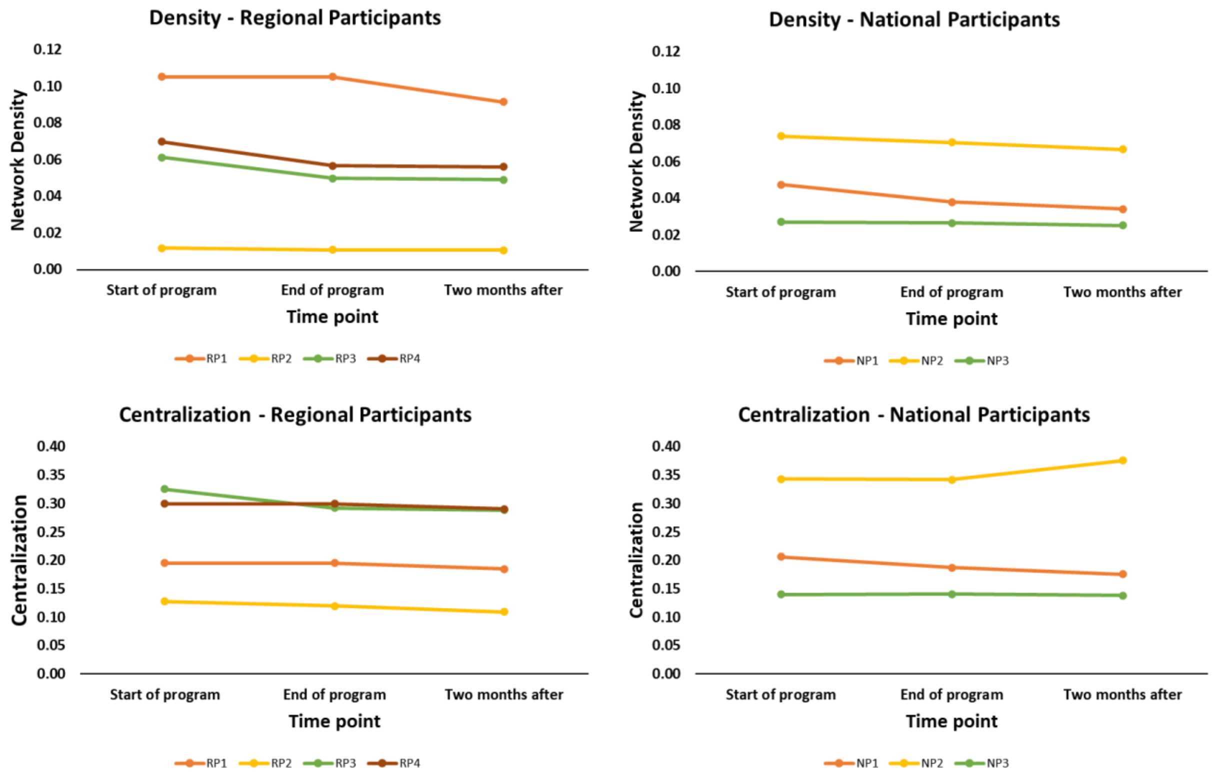

Figure 1 – Network density (top) and centralization (bottom) for participants in the regional I-Corps program (left, 4 participants) and the national I-Corps program (right, 3 participants) just before the start, immediately after, and two months after the program.

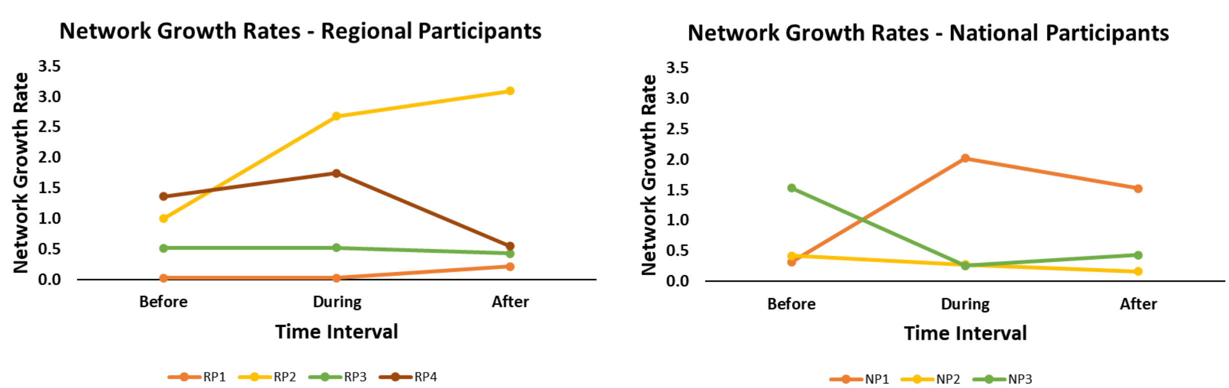

Figure 2 - Network growth rate for participants in the regional program (left) and participants in the national program (right) calculated for three different time intervals – two months before the start of I-Corps, during I-Corps and two months after the end of I-Corps

Figure 2 shows the rate of change in network size for the seven participants, separated by their participation in the regional vs national program. Network size may indicate the extent of resources available to the individual entrepreneur. All participants' networks were found to grow through the program, despite starting at different sizes (note: network size alone is not meaningful for measuring the impact of the program because of this). A higher network growth rate, however, implies that an individual is expanding their network rapidly. The growth rate was not found to uniformly increase after the program despite a more common growth during the program, with 4/7 participants' growth slowing down after the program ended. Additional research is needed to understand this decrease and its potential connection to the participants' commitment to succeed.

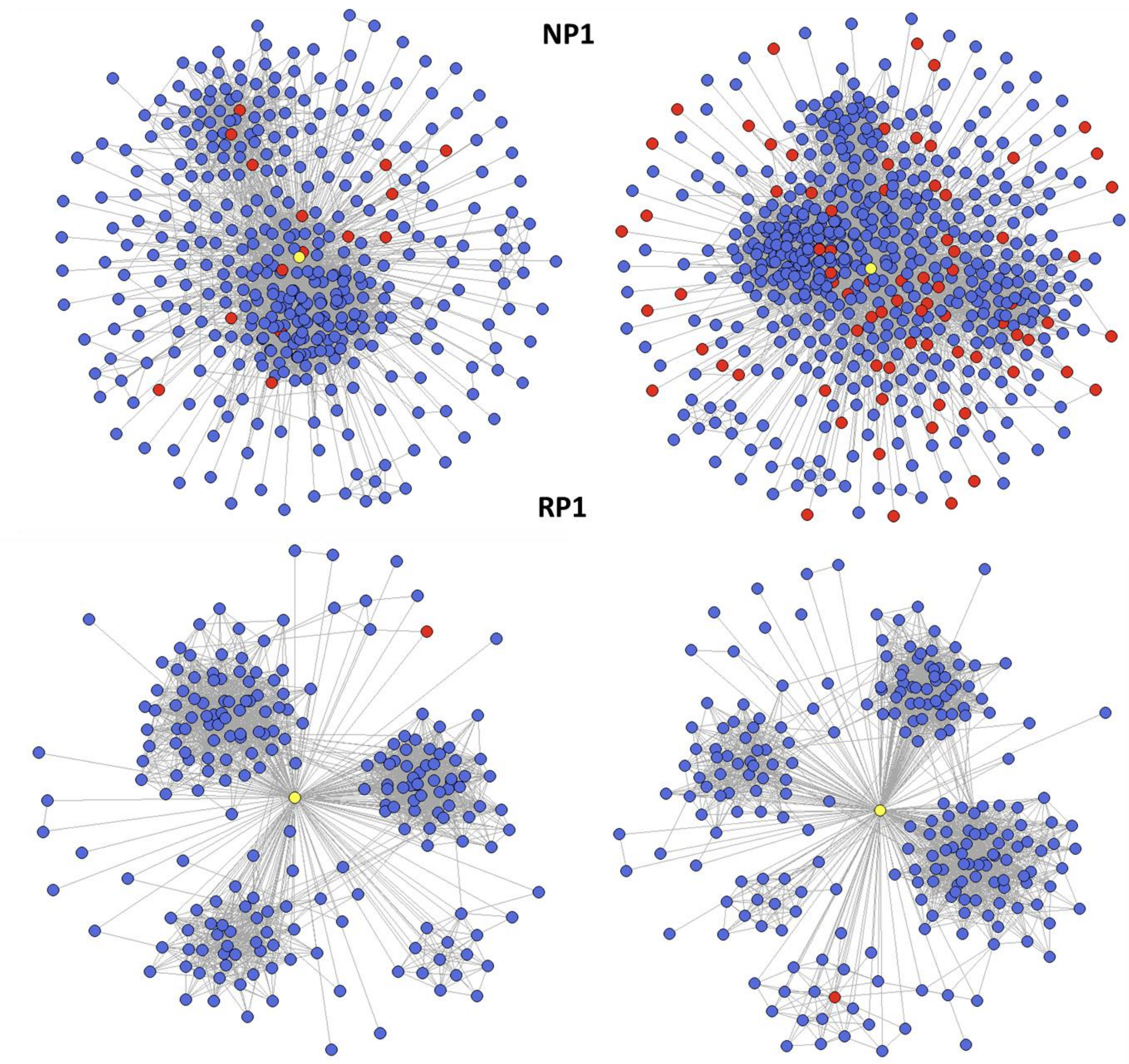

Figure 3– Visual representation of participant networks before I-Corps (left) and two months after I-Corps (right) for NP1 (top) and RP1 (bottom). The yellow node represents the participant, the red nodes are the interviewees, and all other connections are blue.

Comparing national participant NP1 and regional participant RP1 is of particular interest as NP1 was identified as the participant with the best learning outcomes and RP1 was identified as the participant with the worst learning outcomes, defined based on their performance in I-Corps, evaluated by the quality of learning (a qualitative assessment of the participant's final presentation in I-Corps) during the program. Other factors were also considered, such as continued engagement of the team in the project, receiving early funding, filing patents, industrial design rights or trademarks, publishing in peer-reviewed journals, or getting mentioned in news articles. Future work will develop a more formal rubric for participant program performance and entrepreneurial performance to quantitively connect network metrics to success. Figure 3 shows the network graphs for participants NP1 and RP1, with the green node representing the participant, or ego, and the red nodes representing connections that were interviewed during the program. NP1 connected with a significant portion of the individuals that they interviewed for I-Corps, 80 interviewees added out of 148 interviewed. RP1 was only connected to one interviewee and that was someone they already knew before the program.

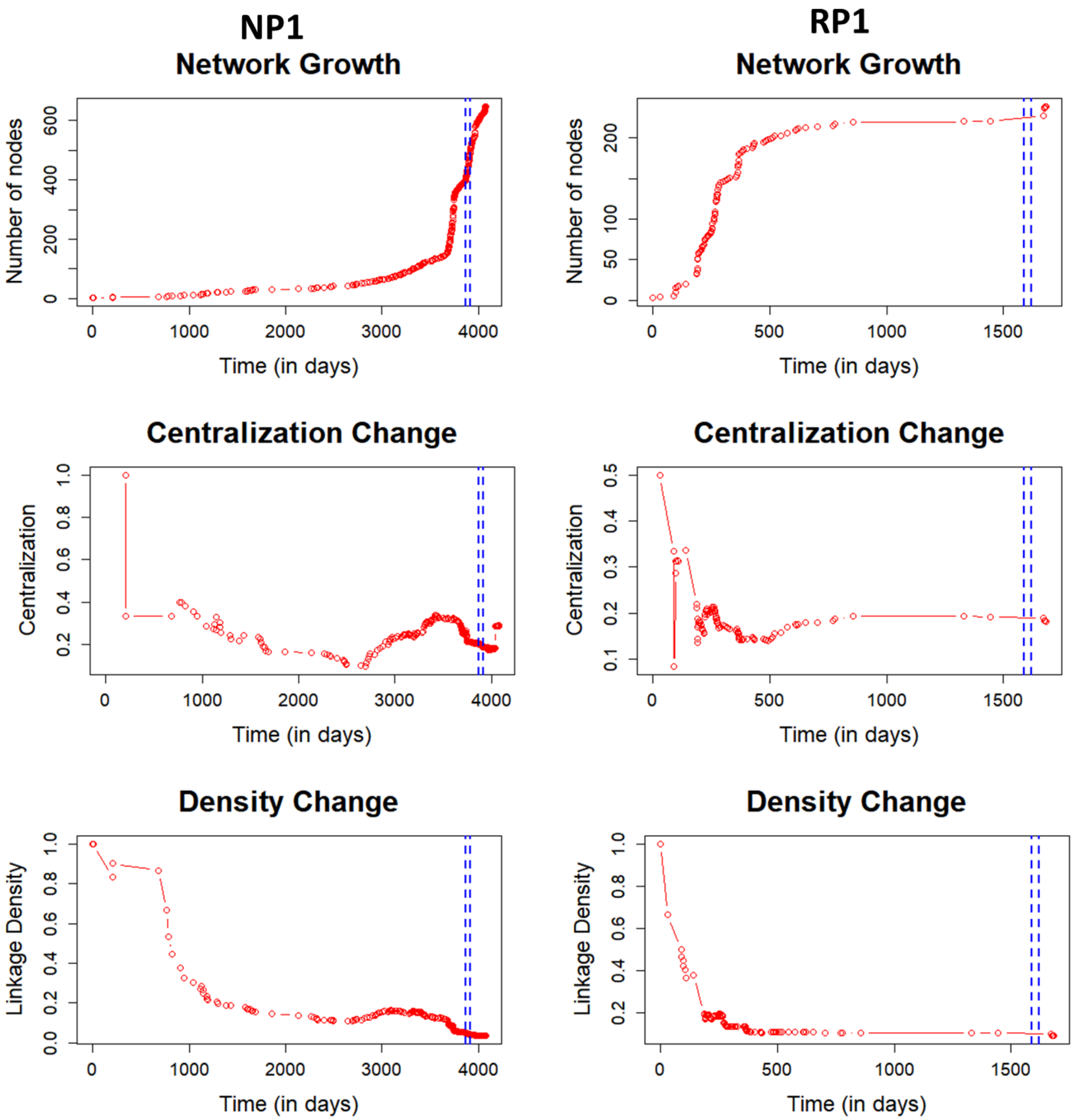

Figure 4- Network growth, centralization, and density change over time (days) for NP1 (top) and RP1 (bottom). The dashed blue vertical lines highlight the time interval when the participant was engaged in the I-Corps program.

Figure 4 shows network growth, centralization, and density change with time (in days) for participants NP1 (top) and RP1 (bottom). The plots show network size and centralization from when the participant first created their LinkedIn profile to the time when they enrolled in this study. The dashed vertical blue lines show the interval when the participant was engaged in the respective I-Corps program. Participant NP1, the participant with the best learning outcomes of our 7 data points, can be seen to have a high network growth rate both during the program and after while the network size for RP1 remains largely unchanged with a low network growth rate around the time of the program. NP1 had a network growth rate of 2.02 during the program (median 0.52, IQR 0.27-1.88) and RP1 had network growth rate of 0.02 during the program. Additionally, network growth rate for participant NP1 increased by more than five times during the program (compared to their network growth rate before the program). No change in network growth rate during the program was observed for RP1. Large decreases in centralization and density are also seen during the program for NP1. For NP1, there was a 20 percent decrease in density (median decrease 7 percent, IQR 3.4-18.7) and a 9 percent decrease in centralization (median decrease 0.48 percent, IQR 0.03-7.78). For RP1, there is no decrease in centralization and density during the program.

It should be noted that national I-Corps participants typically participate in a regional program prior to participating in nationals. Network growth for NP1 shows a sharp increase even before starting the national I-Corps program. This could be attributed to participation in a regional program, preparing them for the national program. The network growth rate of NP1 remains high even after the completion of the program. The higher network growth rate after the completion of I-Corps could indicate that the participant continued the process of refining their business model through additional customer discovery. Future work will incorporate additional participant data to further examine these trends with respect to both the regional and national programs. This will help clarify if things like preparation assistance prior to the national-level program and continued customer discovery after the program play a role in participant success. These early results indicate that a high network growth rate, coupled with a decrease in density and centralization, together are indicative of entrepreneurial success and a participant with access to more diverse opportunities, resources, and information.

Conclusions

Examining structural constructs of I-Corps participants' networks suggests that successful participants access more opportunities and information through rapid network growth. Network growth alone, however, is not sufficient for access to a larger diversity of resources. Decrease in network density and centralization, along with high network growth, might lead to positive entrepreneurial outcomes. Successful outcomes were also linked to distinctive network growth strategies such as preparation prior to the program and continued customer discovery after the end of the program. Future work will establish clear performance criteria for program success and evaluate network growth strategies of additional participants.

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