Accessories or Parts: Technical vs. Managerial Hiring Patterns of Software Start-Ups at Seed Stage

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OBJECTIVES

At the seed stage, software start-ups finally have the external funding needed to strategically grow their organizations. However, they face the critical dilemma of hiring choices. What human capital should they obtain? Should they hire more technical personnel, to speed up product development and innovation, or managerial personnel, to help commercialize the business and facilitate team building? What kind of "outsiders" do these nascent teams trust when carrying out unfamiliar hiring practices? What are the driving forces that lead them to arrive at different human resource decisions?

Under the guidance of these questions, this study aims to discover how the characteristics of software start-ups affect their online hiring decisions at the seed stage. Empirically, this study utilizes a combination of firm-level information and content from individual job postings on the entrepreneurial recruitment platform AngelList Talent. A mix of quantitative analyses including regression, clustering, and sentiment analysis will be performed on this novel dataset. This methodology and empirical choice will supplement the lack of discussion around early-stage hiring decisions in entrepreneurship literature and showcase a sociological interpretation of internet data.

SIGNIFICANCE

In the United States, small business is an integral part of the economy and labor market. According to the 2020 report by the U.S. Small Business Administration, small businesses employed 47.1% of the private workforce, creating 1.6 million net jobs in 2019. Moreover, small businesses' hiring power remains strong despite the impact of the COVID-19 pandemic. In a random sample survey conducted by the National Federation of Independent Business (NFIB) on 613 small business owners, 60% of them plan to fill open positions, which remain at record high levels.

Start-ups show more promising hiring power than other types of small businesses. As the Kauffman Foundation (2010) states, "job growth is driven, essentially entirely, by start-up firms that develop organically." Furthermore, effective hiring decisions in small firms are becoming more important for the economy because they are increasingly knowledge-based (Steward and Hoell 2016; Sels et al. 2006; Cardon and Stevens 2004; Hornsby and Kuratko 2003; De Kok and Uhlaner 2001). This study focuses on the hiring practices of software companies as representative of knowledge-based industries. Software firm characteristics include relatively low capital intensity and an emphasis on tacit, human-capital-embodied resources (Singh 1997; Dodgson 1992). In other words, they invest more in recruitment than asset purchases, fostering a more dynamic hiring market.

The study selects early-stage hiring as its subject. Early-stage employees not only play an integral role in improving productivity and output performance but also heavily influence the climate and identity of the organization in its earliest phase of growth (Steward and Hoell 2016). Despite that importance, current entrepreneurship literature lacks in-depth analyses of early-stage employee hiring. A recent literature review on entrepreneurship by Shepherd et al. (2019) specifically calls for more research on human resource management decisions.

Considering that call, this study makes an important contribution by exploring such decisions in the form of online recruitment using the theoretical framework of human capital resources and social network theory. The human capital resources aspect informs what kind of knowledge and skills are favored by different firms, and the social network aspect reveals the actions taken to acquire new relationships through employment. In this way, the study fills the gap in our understanding of how firms subjectively value human capital resources and how searching and acquiring content drives network formation (van Burg et al. 2021; Ployhart et al. 2014).

For entrepreneurs, hiring needs are multifaceted and complex. Hiring needs to meet the demands of growth while building a functional environment and organizational identities (Steward and Hoell 2016). All these components are critical to firm performance and survival, but few insights have been offered to help with this type of decision-making. This study is unique in offering a transverse section of how hiring choices are made regarding internal characteristics by controlling the external industry environment.

BACKGROUND

Human Capital Resources

Human capital resources are "individual or unit-level capabilities based on individual KSAOs that are accessible for unit-relevant purposes," whereas KSAOs are defined as "knowledge, skills, abilities, and other characteristics" (Ployhart et al. 2014; Ployhart and Moliterno 2011). In the context of this study, technical and managerial hires have mutually exclusive KSAOs. A technical hire, such as a software developer, requires programming knowledge and related skills;

by contrast, a managerial hire, e.g., a sales representative, prioritizes interpersonal skills. The characteristics of software start-ups help to establish clear categorization criteria for technical vs. managerial hiring. More details on this will be discussed in the research design section.

In the process of deciding whether to increase technical or managerial staff, the firm makes a binary decision to purchase human capital resources to support either product development or commercialization. The acquisition of human capital resources is based on the firm's valuation of resources. A recent theory argues that this type of valuation is commonly becoming more subjective (Ployhart et al. 2014; Schmidt and Keil 2013). This links to this study's attempt to define firm characteristics and how they affect the valuation and, therefore, the decision to acquire certain types of human capital resources.

Firms need to allocate appropriate human capital resources to foster innovation because it is a crucial element in software development. Software applications are copyable and resalable products that win the market through innovative features. For small software start-ups, teams are the crucial drivers of innovation (Rose et al. 2015). However, it is unknown whether emphasizing technical hiring while building a team accelerates innovation or impedes collaboration. Therefore, the case studies presented will demonstrate attempts to build a harmonious team that delivers innovation.

Social Network

After identifying the KSAOs that software start-ups want to obtain, the focus will shift to how and why online recruitment is chosen in this context. More employees and employers are moving online for recruitment purposes (Piercy and Lee 2018; Ryan and Ployhart 2014). AngelList, a job information website, caters to start-ups and plays an important role in their online hiring activities. Who recruits on AngelList and why? To provide theoretical guidance on this question, key concepts from the social network and related theory will be discussed.

Organizational founding teams are strongly influenced by the mechanism of homophily in both ascriptive and achieved characteristics. In other words, start-up teams have similarities in demographic characteristics and acquired competencies (Ruef et al. 2003). This homophily is fragile against threats of over-embeddedness. Developed from Uzzi's (1996) definition, embeddedness refers to how entrepreneurs situate themselves in concrete, strong network relationships. It is suggested that embeddedness has a curvilinear relationship with positive outcomes, where over-embeddedness leads to rigidity and prevents entrepreneurs from obtaining new resources and knowledge (van Burg et al. 2021). This study proposes that online recruitment is a way to avoid the negative consequences of over-embeddedness. By recruiting someone out-of-network, the start-up extends its network portfolio at the firm level. Thus, both firms and job applicants seek to mutually expand their networks with AngelList.

The choice to hire online and expand the network may be intentional, but it can also be unintentional or even forced. Since software development requires a complex skillset, it is often difficult to find suitably qualified job candidates. The specific requirements may force entrepreneurs to hire outside of their social networks (Stewart and Hoell 2016).

While AngelList allows start-ups to access a pool of potential employees (and vice versa), the start-ups must engage by posting hiring information. In the "content forms structure" tradition, "the direction of content becomes the driving force for network dynamics," where structure is defined as the structural and relational dimensions of networks and content being resources exchanged through networks (van Burg et al. 2021). This tradition frames two key mechanisms differently from the "structure forms content" and "content and structure coevolve" traditions. Accessing is how the intentional search for resources leads to network change; acquiring is the search to acquire content and use referrals to add strong ties that provide content (Hallen and Eisenhardt 2012; Vissa 2012). In particular, Hallen and Eisenhardt (2012) find that entrepreneurs acquire resources by signaling quality, scrutinizing interest, and indicating scarcity. Thus, engagement, i.e., posting job announcements, can be considered a signal to acquire resources. It is constructed in a way to both filter out unwanted and attract feasible candidates. Furthermore, hiring posts are visible to competitors and investors, who must be considered when crafting these acquisition signals. It is unlikely that different companies have identical job requirements, even within a single industry, or that they would characterize potential candidates in the same way. Therefore, the study focuses on the similarities, nuances, and overall patterns of hiring posts.

In summary, when seed-stage start-ups post jobs on AngelList, these firms are broadcasting their network acquisition intentions to a selected audience. That audience is people with desirable KSAOs who want to join start-ups outside of their interpersonal network. I propose that technical hires are selected mainly for their KSAOs and managerial hires are expected to contribute more to the firm's network. Reflecting on the analogy in the title, accessories help the corporate machine operate more smoothly, while parts upgrade the machine's technical configurations. A machine with a high-end configuration may be inoperable due to a dysfunctional cooling fan, while a machine with the best fan might have minimally acceptable computing power. Between accessories and parts, managerial and technical, which one do software start-ups choose? What kind of "wish list" do they post? To decipher the firm's preference, capability, and preconception in making such decisions, I propose the following hypotheses.

> **Hypothesis 1**: Different characteristics lead to distinctive hiring patterns in preference for either technical or managerial hirings.

As previously mentioned, resource valuation is becoming more subjective, which means there are no clear, standard criteria. Furthermore, structured HR recruiting and hiring practices common to larger firms are not often applied in small firms (Stewart and Hoell 2016; Cardon and Stevens 2004; Hornsby and Kuratko 2003; De Kok and Uhlaner 2001). A high variance of hiring preference is expected among different groups of software start-ups.

> **Hypothesis 2:** Since technical hiring is beneficial to product development, smaller and younger firms are eagerly hiring technical personnel to enhance firm survival.

The software industry is turbulent. To survive, start-ups must have enough programmers to keep up with the rapidly changing environment. However, emerging companies do not have sufficient organizational legitimacy to shoehorn new members into their expectations (Chandler et al. 2005; Aldrich and Fiol 1994; Singh et al. 1986). This may affect how younger and smaller firms word their hiring posts. However, this relationship might be mediated by funding and post-funding age, the indicators of available financial resources.

> **Hypothesis 3a:** A firm in a non-hub area may have distinctive hiring patterns due to disadvantage in geographic-clustered networks.

Geographic-clustered networks are strongly emphasized in entrepreneurship literature. (Shepherd et al. 2019). Thus, firms in non-hub areas without effective geographic networks may want to compensate by using online resources for recruitment. In this context, the hub area includes California and Massachusetts.

Hypothesis 4: Hiring preference is affected by financial resources.

Hiring a new employee is a significant investment that must produce income and divert attention resources (Stewart and Hoell 2016). Therefore, the amount and timing of previous funding are likely to influence hiring practices.

Whether intentional or unintentional, at will or forced, the foundation of this proposal is the choices made by the employers. Hypothesis 1 is predicting general phenomena whereas hypotheses 2, 3a/3b and 4 attempt to build a theoretical architecture. While hypothesis 1 is largely descriptive, the hope is that causal relationships in other hypotheses can be established through a closer look at the textual content in job descriptions and city-level spatial data.

RESEARCH DESIGN

A working paper by Bernstein et al. (2020) reveals AngelList's key metrics, acknowledging it as the largest entrepreneurial online recruitment platform with "3.6 million active job seekers and over 185,000 new jobs listed." Though our access to AngelList's backend data has not yet been granted, dynamic public information is still available through web scraping. The data is rich in volume and nonreactive to the research being conducted. Regarding generalizability, Ewens and Townsend (2020) suggest that AngelList attracts high-quality start-ups, and over 60% of companies raising a seed round had an AngelList profile. Since data in this paper was manually gathered in early December 2021, the types of companies active at that time remain unknown. However, generalizability could be improved if access to backend data is permitted. Ostensibly, data on AngelList is self-reported without a strict systemic auditing process. As a preventive measure, falsification of company information is banned in the recruiter's code of conduct, and violations can be reported by anyone.

At this stage, my research has clear and specific scope conditions and has identified corresponding variables suitable for quantitative research. The topic and research question are framed to take advantage of quantitative research by constructing target variables from theoretical accounts. While AngelList Talent contains a mix of quantitative and qualitative data for each company and its corresponding hiring information, the selected analyzable data is presented in Table 1 below. To test the practicability and comprehensibility of the available data, a pilot study was undertaken on two important variables: hiring positions and company size. Data was collected by locating and exporting variable values in JavaScript (see Appendix ii) and visualized in Python.

Preliminary Findings

Figure 1 provides descriptive statistics of the dataset. Among 288 collected hiring postings, 140 (49%) of them were posted by small companies (1-10 employees), 44 (15%) by medium (11-50 employees), 85 (30%) by large (51-200 employees) and 18 (6%) by X-large (201 - 500 employees). The size categorization is relative, and they all qualify as small businesses under the

U.S. Census Bureau's definition. Company count is also provided for reference and shows that medium-sized companies are hiring more actively than other companies.

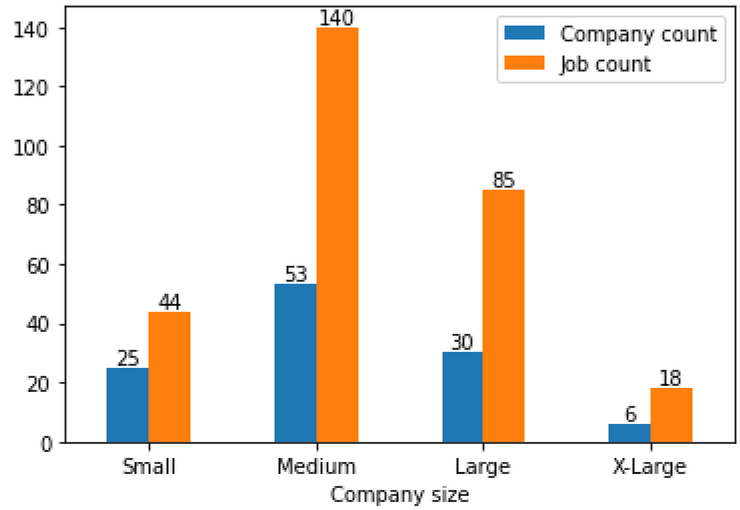

Figure 1

Next, a technical vs. managerial word bank was established and used to categorize hiring positions by keyword matching their titles against the word bank. The word bank was validated by scanning filtered hiring titles for credibility. All collected hiring posts were categorized, and none remained uncategorizable. The selection criteria (Table 2), category definitions (Table 1), and findings (Figure 2) are listed below.

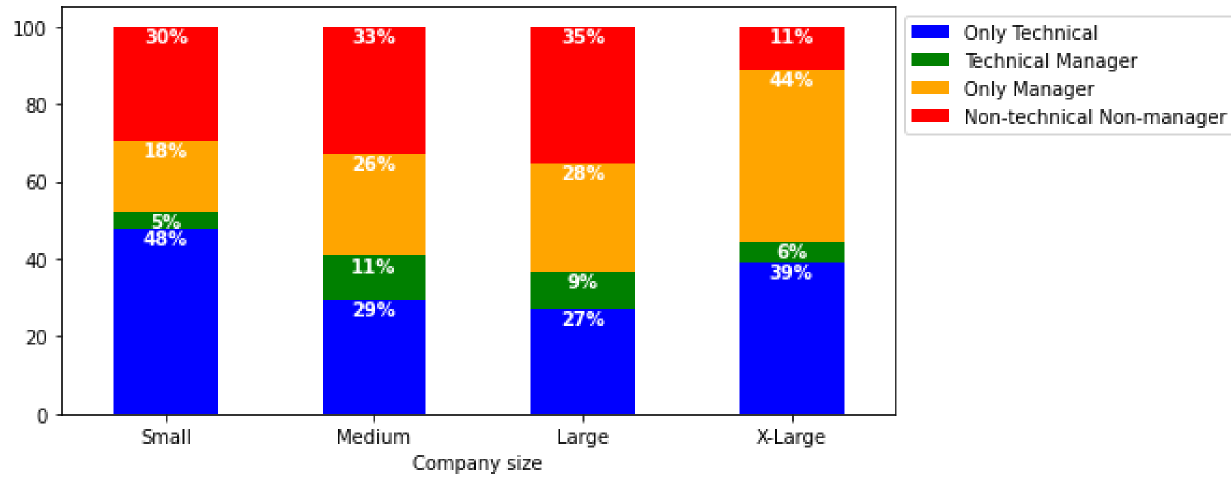

Figure 2

Variable	**Definition**	**Notes**	**Type**
Company type	Scope condition	Conditional search on the website: “worldwide positions” from “seed-stage companies” with “software as market”	/
Hiring posting	Dependent variable / case	Coding: a) technical: “technical” “technical manager” b) non-technical: “non-technical manager” “non-technical” (see below for criteria)	Quantitative: # of coded hiring positions Qualitative (textual): title and content of the hiring post
Company size	Independent variable	Listed as “Company size” on the website	Quantitative (categorical)
Amount of funding	Independent variable	Listed as “amount raised” under the “Funding” section	Quantitative (continuous)
Post-funding age	Independent variable	Calculated from data collection date - last seed round funding date (listed under “Rounds” section)	Quantitative (continuous)

Geographic location	Independent variable	Listed as “Locations” under company profile, coded as hub (California & Massachusetts) and non-hub	Quantitative (categorical)

***Estimated *N* size (active job postings as of 12/5/2021) = 1500-2000 (overall), 800 (software)**

Table 1

	Managerial	Technical
Words *CTO is listed in both word dictionaries because it requires both technical and managerial knowledge/skills	'chief', 'head of', 'vp ', 'vice president', 'manager', 'director', 'lead', 'cto'	'engineer', 'programmer', 'developer', 'scientist', 'architect', 'cto', 'software development'
Technical (technical)	any	none
Technical (technical manager)	any	any
Managerial (non-technical, manager)	any	none
Managerial (non-technical, not manager)	none	none

Table 2

Figure 2 is a stacked bar illustrating the distinctive technical vs. managerial patterns among companies of different sizes. From preliminary findings in Figure 1 and Figure 2, hypothesis 1 seems supported at this stage. While changes may occur when more data points are introduced, the initial findings confirm the overarching direction of the proposal and provide supporting evidence for further exploration in hypothesis testing.

In establishing the word bank, ‘technical hirings’ refers to those positions that require programming ability. Major programming languages and related technical skills include JavaScript, Python, C/C++, Git (version control software) and Linux (Unix-like operating system). These requirements are laid out in detail, thus serving as an effective source for categorization. However, several challenges arose during data collection, and other coders may be introduced in the future to further audit the result. First, the boundary between managerial and technical positions was sometimes unclear and, therefore, subject to personal choice. For example, in the case of data analysts, while they perform programming tasks to analyze data (usually in SQL, Python, and R), these tasks are indirectly related to product development and therefore excluded from the technical word bank. Additionally, start-up job titles are often creative, such as “scientific community evangelist” and “bot experience composer,” and rarely seen in more formal human resources practices. These titles affected data validity and had to be categorized manually. Another concern was the weighting of multiple hiring positions from the same company, which may account for bias towards the more actively hiring companies. To mediate that bias in the future, multiple positions from one company will be weighted proportionally to equal to 1. For example, if a company hires for one technical and one managerial position, each hiring will be adjusted to 0.5 in technical/managerial counts.

In the next step, based on key figures in Figure 2 and Appendix ii, two kinds of quantitative analysis will be used:

a) Linear regression/clustering analysis

Running linear regression for the variables will help identify the correlations which serve as the ground for theory-based verification and falsification. The dependent variable will be hiring positions, and independent variables include company size, amount of funding, the post-funding (seed round) age, geographic location, and founder's degree type. Company size will be treated as a categorical variable due to data availability.

If no correlations can be found, 3-D clustering may help examine the level of similarity between individual cases using continuous variables. In doing so, the x, y, and z axes will be the amount of funding, post-funding age, and the company size respectively. In this process, hiring positions are unweighted data points and shown in different clustering graphs. The empirical reference of the mixed usage of categorical and numerical variables in data clustering can be found in other articles (e.g., Cheung and Jia 2013).

b) Dictionary-based sentiment analysis (on the body text of the job listings)

While a pseudo-dictionary-based method was used in categorizing hiring positions as technical or managerial, this stage relies on an orthodox dictionary-based method. Sentiment analysis is powerful in analyzing the sentiment of textual data in hiring posts to answer hypothesis 2. According to Qazi et al. (2017), sentiment analysis is widely studied and used, consistently contributing to research on customer decisions in the broad area of management. However, the application of sentiment analysis on job postings is rare, possibly due to an assumption that job postings are practical and lack sentimental vocabulary. However, the examples collected from AngelList include numerous postings that use words with a positive sentiment like *amazing*, *passion*, and *fun*. Therefore, it will be helpful to clarify and confirm hypothesis 4 to add to the breadth and coherence of the study. Since the cases will be categorized, a dictionary-based method will help explore the intensity of sentimental words in each category.

The proposed study will use the NLTK-VADER (Valence Aware Dictionary for sEntiment Reasoning) Python package to perform analysis. VADER is a lexicon and rule-based feeling analysis instrument (Bonta et al. 2019). It presents the degree of sentiment by providing a numerical score for each sentiment. A sample of VADER output is displayed below using textual data from the job description for a "scientific community evangelist."

	text	neg	neu	pos	compound
0	We are building the real-world J.A.R.V.I.S. for materials RnD (https://exabyte.io/img/iron-man-creates-material.gif).	0.000000	1.000000	0.000000	0.000000
1	You will help us develop a community around the software framework for the design and discovery of new advanced materials and chemicals (think J.A.R.V.I.S from the well-known movie).	0.000000	0.842000	0.158000	0.571900
2	Work will focus on (1) identifying strategic pathways for community growth, (2) preparing the relevant content including case studies and technical presentation, (3) delivering content and measuring KPI.	0.000000	0.912000	0.088000	0.381800
3	Successful candidates will continue into a leadership role as we grow.	0.000000	0.703000	0.297000	0.585900
4	This is a full-time permanent position.	0.000000	1.000000	0.000000	0.000000
5	product design and concept development	0.000000	1.000000	0.000000	0.000000
6	work closely with the engineering team, relay and explain complex concepts	0.000000	1.000000	0.000000	0.000000
7	see the results of your creative work used directly by the world's leading enterprises	0.000000	0.818000	0.182000	0.440400
8	realize your ambitions and directly define how materials research is done in the future	0.000000	1.000000	0.000000	0.000000
9	work with top-tier human capital in research, engineering and venture capital	0.000000	1.000000	0.000000	0.000000
10	knowledge of chemistry/materials science; MS or PhD in Engineering, Computational Chemistry, Computational Biology, Computer Science or Cheminformatics (or equivalent experience)	0.000000	1.000000	0.000000	0.000000
11	prior work on advanced electronic structure methods (VASP, Quantum ESPRESSO, Gaussian, NWChem, Siesta, or similar)	0.000000	0.875000	0.125000	0.250000
12	prior experience with machine learning is a plus	0.000000	1.000000	0.000000	0.000000
13	ability to learn and apply new concepts rapidly	0.000000	0.753000	0.247000	0.318200
14	prior experience in seeding and scaling technical communities	0.000000	1.000000	0.000000	0.000000
15	strong written and oral communication skills with the ability to effectively collaborate with management and engineering.	0.000000	0.605000	0.395000	0.817600
16	strong time-management and organization skills for coordinating multiple initiatives, priorities and implementations of new technology and products into very complex projects	0.000000	0.858000	0.142000	0.510600
17	strong analytical and problem-solving skills	0.000000	0.548000	0.452000	0.510600
18	Our hiring process and example assignments are explained in more details at https://github.com/exabyte-io/rewotes	0.000000	1.000000	0.000000	0.000000

Figure 3

The job description was scraped from the website and saved into a text file. Then, every sentence was separated by either a line break or period and analyzed by VADER. VADER produced negative, neutral, and positive scores for each sentence. This study aims to discover if the urge to hire technical personnel is stronger among smaller companies. While it is not a perfect measurement, considering the challenge of qualitatively determining large-scale data, higher positive scores indicate stronger motivation and higher standards in hiring. The numeric positive scores and descriptive statistics will then generate new continuous variables for the analyses mentioned in a).

In all analyses, variable selection is based on availability and credibility. In addition to the collected data categories, AngelList provides founders' names and profiles, geographical locations, and job details (e.g., full-time/part-time, remote/in-person, salary range, years of the required industry experience). However, since some employers choose not to provide such information, these data lack reporting consistency and raise questions about their empirical usage. For example, 12% of job postings do not offer a salary range, and 8 % do not provide a geographical location in the current data set. However, most locations provided are in the U.S., which helps test hypothesis 3. Further evaluation of data credibility and potentially omitted variables will be undertaken once a more complete dataset is obtained.

BROADER IMPACT

Seed funds help firms surmount initial hurdles and act as a growth accelerator (Krishna et al. 2016). At the same time, the seed fund stage is a critical moment for nascent firms because a high percentage of firms fail after their first public funding round (Eisenmann 2021). Considering the new resources these software start-ups obtain, their desire to grow, and the appeal to future investment partners, it is useful to observe how this relatively creative HR practice unfolds.

A hiring post can be a firm's wish list, a candidate's ambition, or a staged performance for investors and competitors. With promising preliminary findings, this proposal delivers a holistic examination of long-standing organizational theories with a modern set of data and toolkits. The results of this research demonstrate the value of using dynamic data to pinpoint understudied socioeconomic problems and fill literature gaps. I hope to publish in authoritative journals including *Small Business Economics* and *Journal of Business Venturing*.

This paper also serves as a reflective piece for entrepreneurs and venture capitals. Entrepreneurs are faced with time and cognitive limitations (Stewart and Hoell 2016; Sels et al. 2006; De Kok and Uhlaner 2001; Bird 1988). The anticipated results of this proposal will offer them a better understanding of common HR practices among different types of start-ups and the potential to make better choices for more effective team building.

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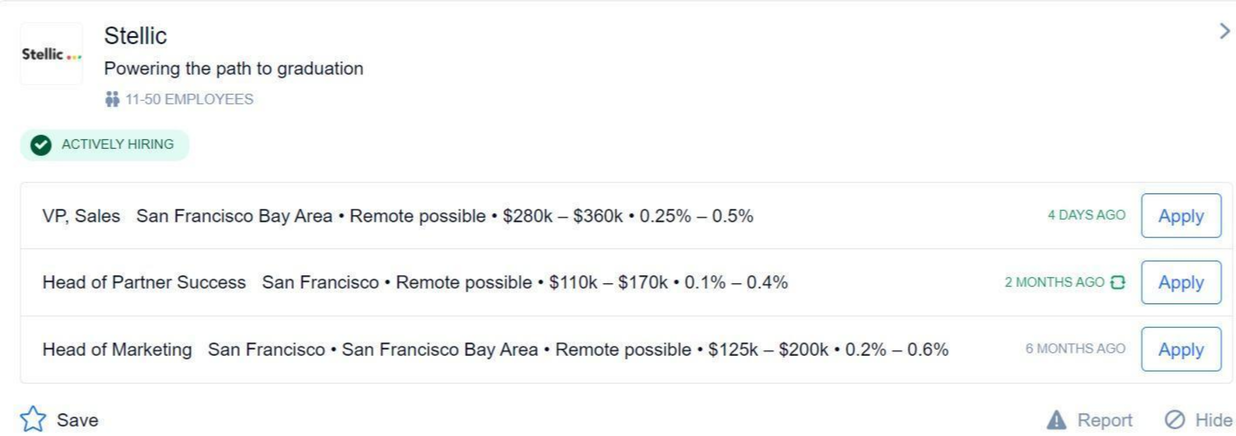

Appendix i

companyName	companySize	tagline	title	details	manager	technical	technical-manager	only-technical	only-manager	neither
Recurate | Resa	35	Recurate e	Brand Success Manager	Remote possible • $60k –	1	0	0	FALSE	TRUE	FALSE
batelle.com	35	Teach pare	Senior Sales Consultant	Remote possible • $45k –	0	0	0	FALSE	FALSE	TRUE
Stellic	35	Powering t	VP, Sales	San Francisco Bay Area •	0	0	0	FALSE	FALSE	TRUE
Stellic	35	Powering t	Head of Partner Success	San Francisco • Remote p	1	0	0	FALSE	TRUE	FALSE
Stellic	35	Powering t	Head of Marketing	San Francisco • San Fran	1	0	0	FALSE	TRUE	FALSE
WREX (Global E	35	Using AI/M	VP of Sales for Global B2B Marketplace (/	New York City • London •	1	0	0	FALSE	TRUE	FALSE
WREX (Global E	35	Using AI/M	Software Developer required for Global B2	California • Los Angeles •	0	1	0	TRUE	FALSE	FALSE
WREX (Global E	35	Using AI/M	Marketing Manager sought for Global B2E	Los Angeles • San Franci	1	0	0	FALSE	TRUE	FALSE
Prophecy.io	35	Low Code	VP Marketing	Palo Alto • $250k – $320k	1	0	0	FALSE	TRUE	FALSE
Prophecy.io	35	Low Code	Director of Product Marketing	Palo Alto • $150k – $180k	1	1	1	FALSE	FALSE	FALSE
Prophecy.io	35	Low Code	Staff Data Engineer - Product Developme	Palo Alto • $200k – $240k	0	1	0	TRUE	FALSE	FALSE
Repool (YC S21	5	Making he	Head of Marketing	New York City • Brooklyn	1	0	0	FALSE	TRUE	FALSE
Repool (YC S21	5	Making he	Senior Software Engineer (early hire)	New York City • San Fran	0	1	0	TRUE	FALSE	FALSE
Lively	125	The Model	Director, Product Operations	San Francisco Bay Area •	1	1	1	FALSE	FALSE	FALSE
Lively	125	The Model	Sr. Information Security Manager	San Francisco Bay Area •	1	0	0	FALSE	TRUE	FALSE
Lively	125	The Model	Sr. Product Manager	San Francisco Bay Area •	1	0	0	FALSE	TRUE	FALSE
Mosaic	35	Mosaic ma	Design Director	New York City • Remote p	1	1	1	FALSE	FALSE	FALSE
Mosaic	35	Mosaic ma	Sales Development Representative	New York City • Remote p	0	0	0	FALSE	FALSE	TRUE

Appendix ii