Artificial Intelligence in Venture Capital Industry: Opportunities and Risks

by

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Abstract

Artificial intelligence - making machines intelligent - is a methodology to build, train, and run machines that are capable of making decisions on its own. Artificial intelligence technologies are gaining significant adoption across a wide range of activities in an organization across different industries. This is fueled by increasing focus on data-driven decision-making methods for all kind of tasks (external or internal) in an organization.

Venture capital industry - traditional sub-segment of financial services industry - works heavily on human interactions and relationships. Venture capital investments are considered high-risk, high-return asset class. Venture investment decision-making could be optimized by machine learning applied to previous deals, company data, founder data, and more. It is quite possible that a system could analyze founder personalities, company metrics, and team attributes and improve venture capitalist's decision-making.

This thesis is an attempt to analyze and breakdown venture capitalist decisions and understand how Artificial Intelligence tools and techniques could be utilized by VCs to improve decision-making in venture capital. By focusing on the decision-making involved in the following eight value chain areas of a venture capital firm - deal sourcing, deal selection, valuation, deal structure, post-investment value added, exits, internal organization of firms, and external organization of firms, we could discover the extent to which artificial intelligence tools and techniques could be used to improve human decision-making in the venture capital industry. Subsequently, we could also identify how artificial intelligence could be practically used in such decision-making scenarios and also the benefits and associated risks involved in using artificial intelligence system in venture capital decision-making.

Thesis Advisor: Michael Cusumano

Title: Sloan Management Review Distinguished Professor of Management

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Acknowledgement

My journey at MIT has been a roller coaster ride trying to balance my aspirations to learn from, participate, and engage with the best and brightest minds in the world. I sincerely thank my parents, my sister and brother-in-law, my three months old niece, and my close friends who supported me in tough times and motivated me not to give up and produce the best outcomes.

Special thanks to Professor Cusumano for being my advisor for this topic and trusting me that I would find a way to complete my research work despite I had no functional knowledge and experience working in venture capital industry. I am highly grateful to him for supporting me to research on this risky but interesting topic and giving me the freedom to explore and strengthen my knowledge in this area.

Last but not the least I would thank Joan Rubin, William Folley, and the entire MIT SDM staff for supporting my all my decisions and for being there for me always.

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List of Abbreviations

AI – Artificial Intelligence
ML – Machine Learning
VC – Venture Capital
VCs – Venture Capitalists
LP – Limited Partner
GP – General Partner
EIR – Entrepreneur in Residence
MD – Managing Director
LPA – Limited Partnership Agreement
IPO – Initial Public Offering
IRR – Internal Rate of Return
M&A – Mergers and Acquisitions
CEO – Chief Executive Officer
CTO – Chief Technology Officer
CIO – Chief Information Officer
GTM – Go-to-market
CRM – Customer Relationship Management
RPA – Robotic Process Automation
RWA – Risk-Weighted Assets
MWA – Margin Value Adjustment
NLP – Natural Language Processing
PE – Private Equity
DCF - Discounted Cash Flow
SEC – Securities and Exchange Commission

Chapter 1: Introduction

Topic introduction

Artificial intelligence (AI), particularly Machine learning (ML), currently influence our lives and our civilization more than ever. There are many application areas of AI technology and limitless possibilities. Because of computing infrastructure improvements, specific AI algorithms already perform better than human experts today. Why is AI (the most crucial general-purpose technology of our era) is such a big deal? Firstly, humans know more than we can tell today. Secondly, Machine learning systems are often excellent learners as they can achieve super-human performance in many activities. In narrow, well-tested areas of application, such as driverless cars and the specific regions of medical diagnostics, the superiority of AIs over humans is already established. Increased use of intelligent technology in different arenas offers excellent potential, including fewer road traffic accidents, fewer mistakes in the medical treatment and diagnosing of patients and analyze dynamics of startup ecosystem to automate and improve decision-making processes related to funding a startup. As almost all industries catch up with the technological advances AI offers, and as companies seek to implement them in some way into their businesses and systems, AI is set to become more than a trend - it will become a general-purpose technology (like electricity, steam engines) for years and even decades to come.

Statistically, roughly around 20% venture investments succeed, with 5-10% yielding results of 10-20x and only 1% yielding results higher than 100x [1]. Approximately eighty percent of the deployed capital is misapplied efficiently and yields no returns. In 2016, global VC market totaled approximate $170B compared to around $150B in 2015 [2], signifying an increase in venture investments and relative ease of funding for startup companies. It's one of the big reason venture funds have underperformed the stock market (S&P, NASDAQ, Russell 2000) in some past years [3]. Venture capital investments are considered high-risk, high-return asset class. Venture investment decision-making could be optimized by machine learning applied to previous deals, company data, founder data, and more. It is quite possible that a system could analyze founder personalities, company metrics, and team attributes. Not only selecting best investments, but machine learning could also be potentially used to solve other challenges in a venture capital firm - finding co-investors, maximizing value to investors, providing strategic and operational guidance to a startup.

Most academic studies have focused on analyzing factors that are correlated with a startup success. However, very few academic research has been done to consider an entirely quantitative approach to venture capital. Traditionally, venture capital industry had been a closed network in which few venture capital firms had access to the disruptive companies of the world. In recent years, few emerging venture firms have been testing and adopting analytical ways to reshape the art of venture capital and turn it into more of science. These firms are resorting to varying degrees on what are, for venture capital industry, radical new uses of software and data to help guide their investments. Google Ventures, the venture arm of Alphabet Inc., is using quantitative algorithms to aid investment decisions. Early-stage venture capital firm SignalFire, launched in San Francisco in 2015, mines vast repositories of proprietary databases in real time, such as such as monitoring capital flows into startups and movements of key employees, to identify investment targets and support their venture decisions. Correlation Ventures, a venture capital firm with over $350 million under management, brings proprietary data analytics and predictive computing into its decision-making on joining deals as a co-investor.

AI holds incredible promise for venture capital industry and, in turn, the startup ecosystem. It could be used to funnel investments into more viable companies, generate real economic value, create stable jobs, and catalyze innovation. 0.2% of new businesses receive VC funding, and 50% of US IPOs are venture-backed [4]. Venture Capital is key to the emergence of the most innovative ideas in today's economy. Using the latest technology, especially advancements in Artificial intelligence, to find the best deals and help startups can make venture investors stand out from the crowd.

This thesis is an attempt to analyze and breakdown venture capitalist decisions and understand how AI tools and techniques could be utilized by VCs to improve decision-making.

Thesis Scope and Approach

The current research work on this thesis is focused on analyzing working methodology of institutional venture capitalists (and venture funds) and their investment decisions only related to the following eight value chain areas in venture capital - deal sourcing, deal selection, valuation, deal structure, post-investment value added, exits, internal organization of firms, and external organization of firms (mainly dealing with relationships with investors).

The research approach of this thesis comprised of the following steps: First, review venture capital industry ecosystem and about artificial intelligence technology and adoption study in different industries via primary as well as secondary research methodologies. The research methodologies include reading venture capital books, enrolling in related MIT Sloan courses, reviewing industry reports, articles and blogs, attending relevant club sessions, conducting extensive interviews with academic and industry experts, and reviewing related academic research. After data and insights collection from different sources, frameworks and approaches from aforementioned disciplines in Artificial intelligence adoption, Task suitability assessment framework for machine learning, and strategy frameworks have been used to synthesize information and present research findings.

Chapter 2: Introduction to Venture Capital

What is Venture Capital?

Venture Capital is a type of private equity financing provided by individual investors (Limited Partners) to private companies that have potential to develop into successful businesses in exchange for equity (part ownership of business) [5]. Venture capitalists, who manage the capital provided by these investors under the umbrella of a venture capital fund, finance new and rapidly growing businesses (startup companies) and provide strategic guidance and assistance in the development of new products or services. Since such groups carry a high level of risk and uncertainty, venture capitalists invest large amounts of private capital based on long-term prospects (selling the company or holding an initial public offering) rather than short-term returns.

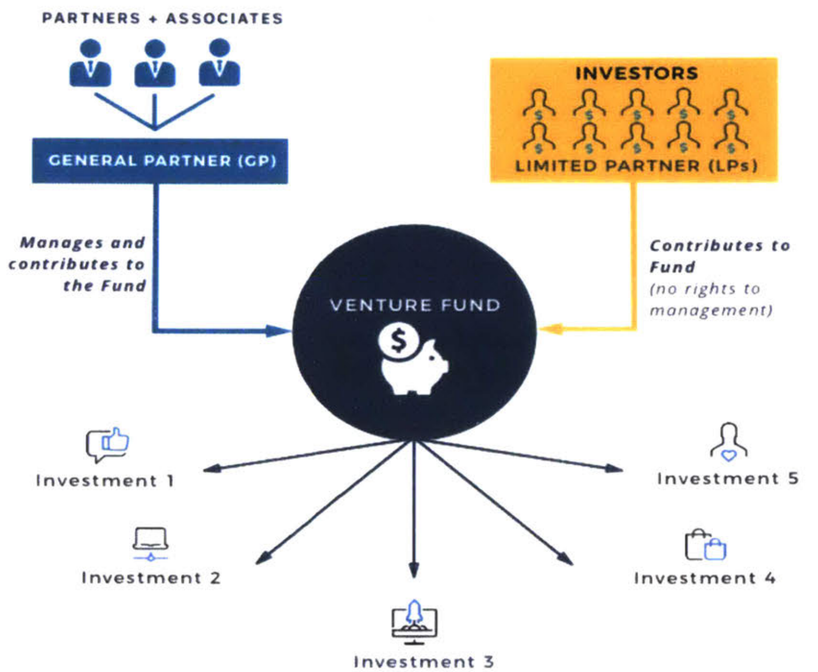

Figure 1: Structure Of A Venture Capital Firm [6]

What constitutes a Venture Capital firm?

A typical venture firm consists of a hierarchal organization structure. The leading person in a venture capital company is usually either a Managing director (MD) or a General partner (GP). In some cases, these titles have an additional prefix - founding general partner or executive managing partner - depending on the seniority level compared to other managing directors or general partners. A managing director or a general partner makes the final investment decision and provides strategic guidance to portfolio companies as a

Board member of the portfolio company. Partners (also referred as principals or directors) are not actually partners in the firm but are often junior deal investment professionals who are involved in specific aspects of the investing process, such as deal sourcing, valuation, and are sometimes involved in internal operations of the firm (recruiting, operations, sales and marketing functions). Next in line are Principals or Directors - junior deal professionals with some deal responsibility - have some power but requires support from Managing director to make a decision. Associates work with one or more deal partners (usually a Managing director) and help source a deal, do due diligence, and write investment memos about potential investments. Analysts are the junior most people in the firm (usually recently grads from college) who possess limited power and routinely crunch numbers and write memos.

Some large venture capital firms may have diversified venture partners or operating partners working on a part-time basis with the VC firm who are experienced entrepreneurs and have deep industry expertise. They are usually involved in sponsoring a deal (along with the support of a Managing director) or managing an investment as a chairman or board member. Entrepreneurs in Residence (EIR), experienced entrepreneurs, are another type of part-time member of the VC firms. They usually help the VC with networking, introductions, and due diligence.

Venture Capital operational process breakdown

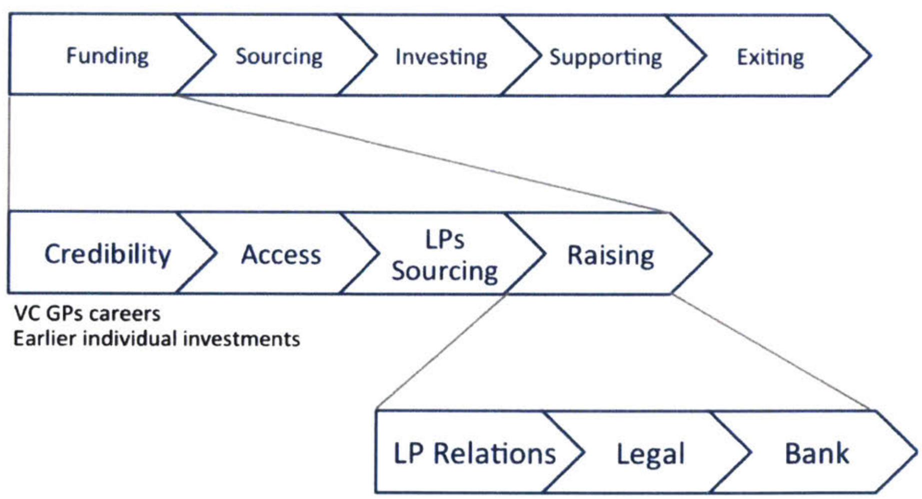

Figure 2: Fundraising from LPs Process [7]

Venture capitalists raise money (see figure above) from around 8-10 Limited Partners (LPs) - pensions funds, high-net-worth individuals, large corporations, banks, charitable organizations, insurance companies, institutional investors, funds-of-funds, family offices, educational endowments. VCs and their investors (LPs) negotiate and establish a complicated contract known as limited partnership agreement

(LPA) that highlights the working relationship between a venture capitalist and an investor during the period of a venture fund lifecycle. Venture capitalists raise money from Limited Partners (LPs) for investment in high-potential but high-risk companies. A Venture capital fund (limited partnership investment fund) is said to be closed when LPs promise to provide a certain amount of capital at specific periodic capital provisions (also known as capital calls, drawdowns, or takedowns) based on a set schedule or at the discretion of a General Partner. LPs promise to provide capital (committed capital of the fund) at defined intervals over the period of the venture fund [8].

Figure 3: Venture Investment Funnel [9]

After a venture capital fund is closed, VCs start searching, learning, investing, and exiting in various companies (see figure above). Most venture capital firms fetch returns from a small percentage of investment deals. VCs first start looking and interacting with companies. This process of searching and interacting with potential startups or enterprises is called Deal Sourcing. A typical VC firm sources around 400 companies from different sources - VCs network, serial entrepreneurs, university clubs, other VCs [10]. Associates are primarily involved in meeting with entrepreneurs and analyzing potential leads. They review potential opportunities and decide whether to reject, contact entrepreneur for more information or recommend the chance to one of the partners in the venture capital firm. The primary goal of deal sourcing is to get high-quality startup deals. VCs generate leads both from outbound sourcing (professional network and events) as well as inbound sourcing (entrepreneurs reaching out to VCs) as seen in the figure below [8]:

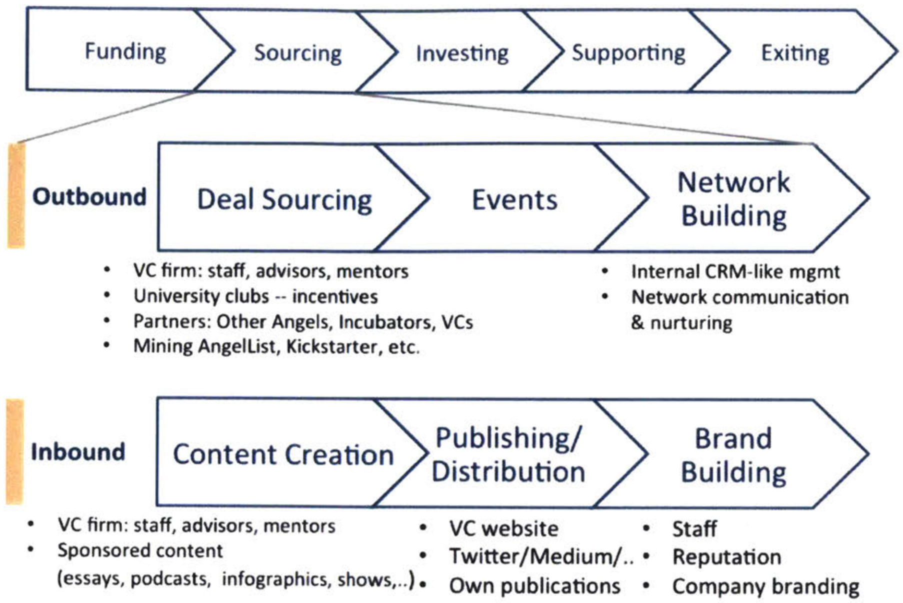

Figure 4: Deal Sourcing Process [7]

After sourcing potential deals, VCs start learning more about the companies and screening the deals. Initial screening and elimination is the first step of funnel filtering. The primary filter used at this stage is investment thesis - the beliefs that act as guiding light for the VC firm. The investment thesis can be based on markets, business models, strategy-driven, startup stage, regional, technology driven. Deals that pass through the initial screening process proceeds to the due diligence process. There are multiple stages of due diligence process (preliminary, 2nd level, and final due diligence stages). Time and resources from the VC firm grow as a deal moves forward in the investing process. Deals that successfully pass through the final due diligence stage are considered for financing. Term sheets ("Letter of Intent" or "Agreement in Principle") are designed to capture the assessment from due diligence stages and defines the economics and control mechanisms of the investment deal between the VC and the entrepreneur [8]. The terms set and negotiated in the Term sheet defines the final legal deal structure and acts as a proxy for the relationship between the VC and the entrepreneur. Once the Term sheet is negotiated and signed, some VC firms may have a final approval process from the investment committee before closing the deal. The last part of closing the deal if the process of drafting the definitive agreements. Generally, lawyers do most of the work to prepare these legal documents. They will take the term sheet and negotiate lengthy documentation generated from the term sheet. In the best-case scenario, these legal agreements are signed and money is released from the VC firm to the bank account of the entrepreneur.

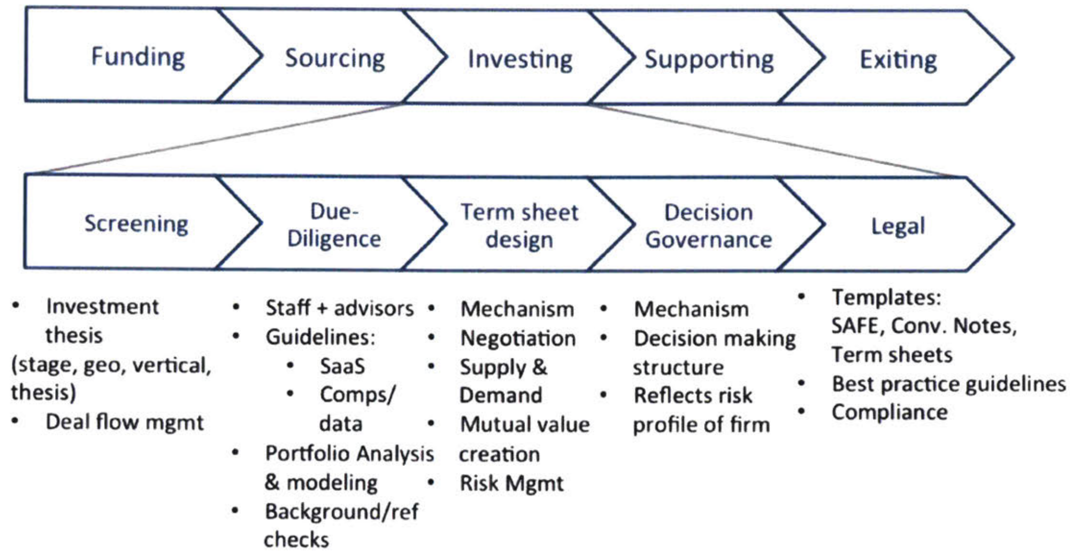

Figure 5: Investing Process [7]

After an investment deal is finalized and money released, VCs actively provide strategic guidance and support to the startup company. The post-investment support provided by a VC firm decreases with more deals volume per firm due to the limited bandwidth of resources in a VC firm [7]. There are some VC firms who have built repeatable practices in-house to support portfolio companies in growth and scale. Post-investment value-add services form a critical value-generating component of venture investments. Some VC firms have specialized investment focus areas and may provide tailored services to individual needs of the portfolio companies that many times supplements the capabilities of these companies. VCs provide different forms of supporting services to their portfolio companies - serving on the board and providing strategic guidance, providing expert guidance, the network of experts and other venture partners, talent recruitment, skill development, process formation and streamlining, connecting with potential customers, operational support, support from other portfolio companies [8] [11].

Prominent venture capital firm Andreessen Horowitz has made investments in many successful startups - Airbnb, Facebook, Skype, Twitter, Instagram, and more [12]. VCs provide their portfolio companies organized support through their support teams that are trained in marketing, technology, recruiting, and business development. They also help portfolio companies with preparing negotiations, customer development, providing suppliers. First Round Capital is another example of a venture capital firm with seven partners and more than $400 million assets under management that offers a wide range of initiatives to support their portfolio companies. They organize yearly CEO, CTO summits in which executives from all of their portfolio companies come together and share their learnings [12].

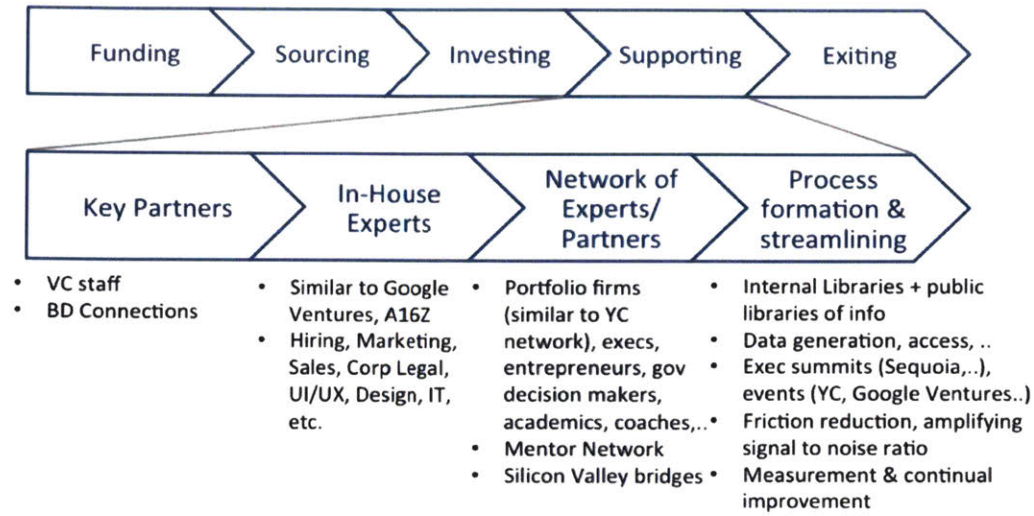

Figure 6: Startup Support Process [7]

Lastly, venture capitalists are in the business of generating returns to LPs with high Internal Rate of Returns (IRR). They need to cash out and focus on possible liquidity events for successful portfolio companies. A successful exit is the last milestone for the VC and in many cases for the startup company. They look for possible liquidity options for desired portfolio companies - acquisitions and IPOs (Initial Public Offering), exiting through secondary markets or existing shareholders, raising mezzanine or private equity financing if a portfolio company is under financial distress. Unless the startup company has received acquisition bids, VCs leverage specialized M&A firms to find potential buyers [8]. For IPO, VCs can help in finding an investment banker who could act as an underwriter and support the startup in the IPO process [7].

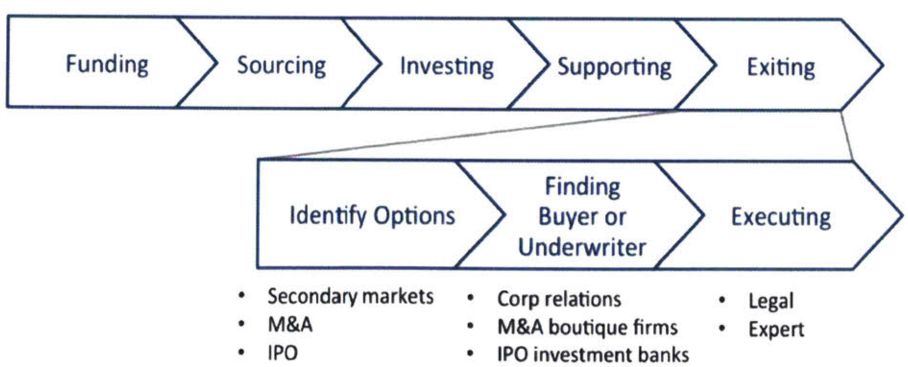

Figure 7: Startup Exit Process [7]

Primary stakeholder analysis

The primary stakeholders involved in a venture capital fund are: Limited Partners (LP), Venture Capitalist (Partners), and founders of the portfolio companies. The below diagram shows the value network amongst these primary stakeholders:

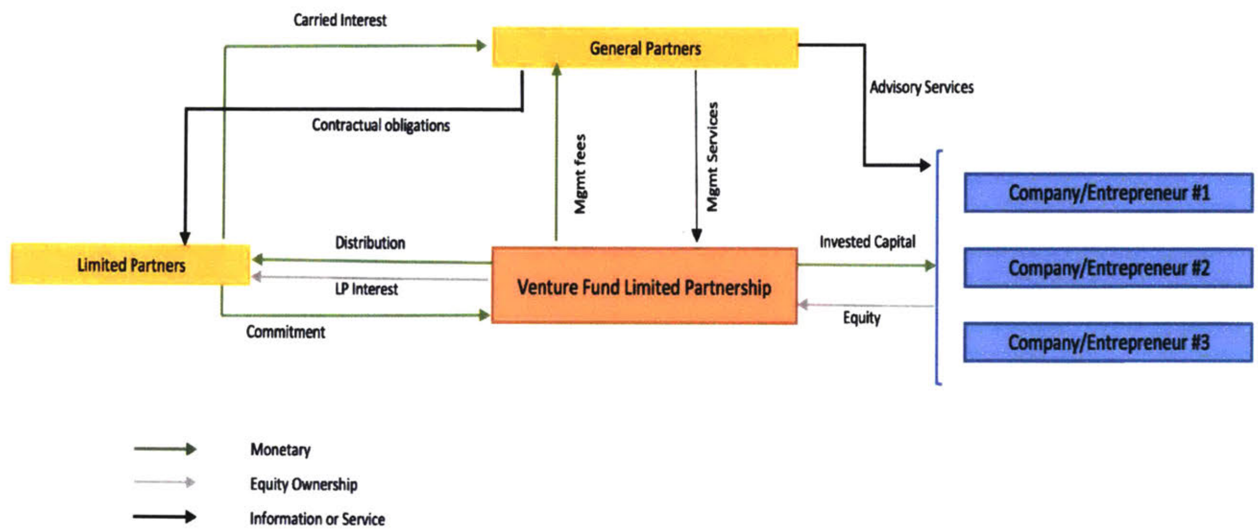

Figure 8: Stakeholder Value Network

(a) Venture Capitalist (Partners): VCs have different motivations and financial incentives during different stages of a venture capital fund cycle depending on the commitment period (length of time a VC has for searching and investing in new companies), investment term (fund active duration), reserves (amount of investment capital allocated to each portfolio company), or cross-fund investing (managing multiple funds). VCs also owe fiduciary duties to their management team, to GPs, LPs, and to the board of every portfolio company. The compensation dynamics of a particular venture fund often impacts the behavior of a VC during the lifecycle of a venture capital firm. It is important to understand how VCs makes money in this business from different sources [8] [11]:

- *Management Fees*: VCs salaries comes from the management fees of their funds (typically between 1.5% and 2.5% of the total amount of money committed to a fund). This fees is paid out annually and funds most of the operations of the firm (salaries, travel, rent, general expenses). The fee percentage is usually inversely proportional to the size of the venture capital fund. In many cases, venture capital firms raise funds more frequently or may have multiple different fund vehicles (early-stage fund, late-stage fund). In such cases, the fees stack up across funds. The venture capital fund gets its management fee irrespective of its investment success. Over the long term, this might affect the raise another fund.

- *Carried Interest:* The real money that a VC makes is through carried interest or carry (the profit that VCs get after returning money to LPs) even though the management fees can be a substantial amount of money. If the fund size is $100 million, most VCs get 20% of the profits (or 20% carry) after returning capital although some extremely successful funds take up to 30% of the profits. Let's say the fund return 3x capital ($300 million). In this case, the first $100 million goes to the LPs, and the remaining $200 million is split 80% to the LPs and 20% to the GPs [8].

- *Reimbursement for Expenses:* VCs also earn some income as reimbursement expenses from their portfolio companies for operational expenses. These expenses could be related to travel, stay, and other reasonable expenses associated with board meetings to the portfolio company.

(b) Limited Partner (LP): The limited partners (LPs) invest their capital into venture capitalists and utilize experience, industry experience and strategy of a VC firm to generate on average 3x absolute returns on the invested capital. Most institutional investors expect premium returns relative to other asset alternatives (in most cases stock market) [13]. Top tier venture LPs care less about IRR (Internal rate of return) if they can get high net returns.

(c) Entrepreneur: Apart from financing the company, an entrepreneur wants VCs (see figure below) who are experienced, rational and well-connected individuals and who offer strategic guidance, and connect with customers, other portfolio companies, or other investors. Entrepreneurs look for VCs who are active participants in their business and not just merely act as financiers.

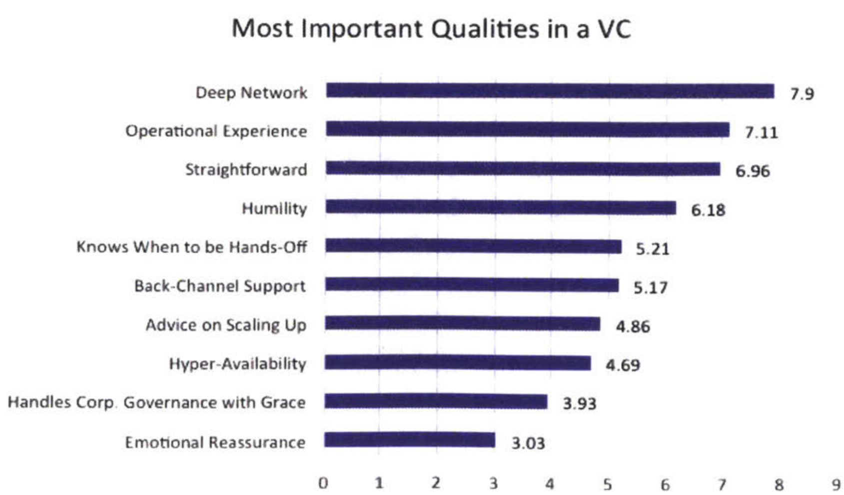

Figure 9: Qualities Entrepreneur wants in a VC [14]

Types of Venture Capital firms

There are different types of venture capital firms [8] [11], either institutional or corporate venture capital groups inside a large corporation, depending on different attributes:

- **Stage** - VC firms invest based on different rounds or stages of venture capital (see figure below) from pre-seed, seed, series A, B, C, D, and beyond. Pre-seed, seed, series A investments are given to early-stage companies, series B and C are mid-stage companies, and series D and beyond is a late-stage company. VC firms are often termed as *micro VC fund* (angel investors with one general partner), *seed-stage fund, mid-stage fund, late-stage fund* depending on investment stage and size of venture capital.

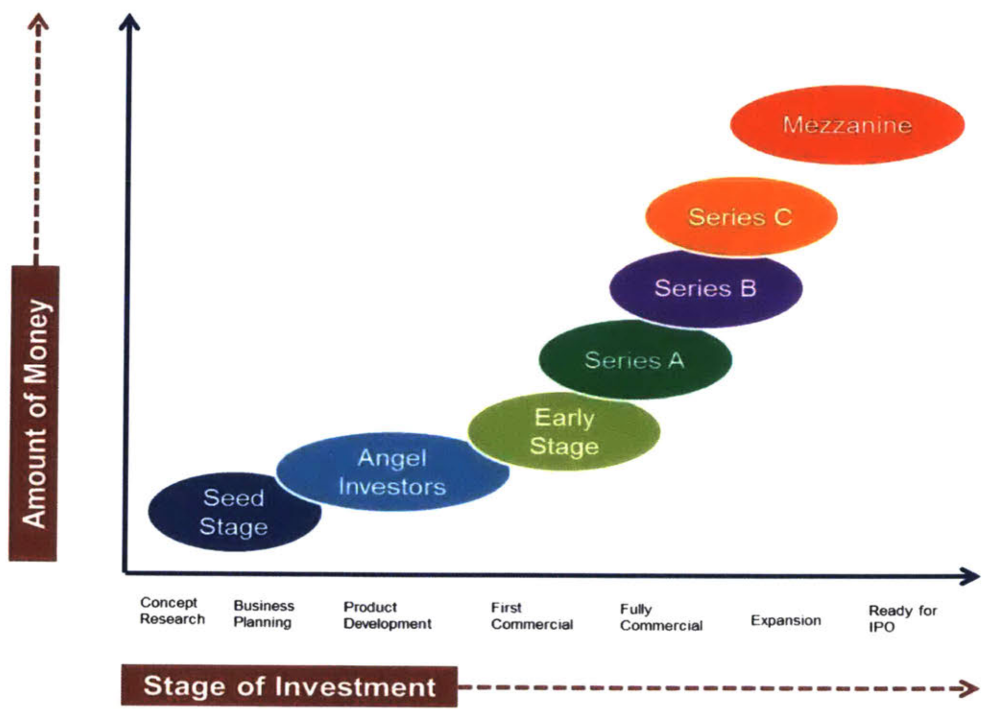

Figure 10: Startup Fundraising Stages[15]

- **Specialization** - These types of VC firms focus on specialized areas – some firms focus on business to businesses companies while other focus on business to consumer companies. Also, VC firms could differ based on specialization in domain, industry, knowledge expertise, service offerings to portfolio companies.

- **Generalist** - These type of VC firms take a more generalist approach to venture capital and diversify their investments across different industries and sectors. In many cases, such firms are comprised of generalist partners rather than a diversified group of industry expert partners [16] .
- **Geography** - These types of VC firms specialize in particular geography based on their expertise or professional network and on different funding cultures in different markets.
- **Fund life cycle** - The average venture capital fund cycle is about 10 years (ranges from 8 to 12 years) [8]. VC firm's investment strategy differs based on the age of venture fund. A young fund might invest in more risky ventures compared to the one that is near its end.

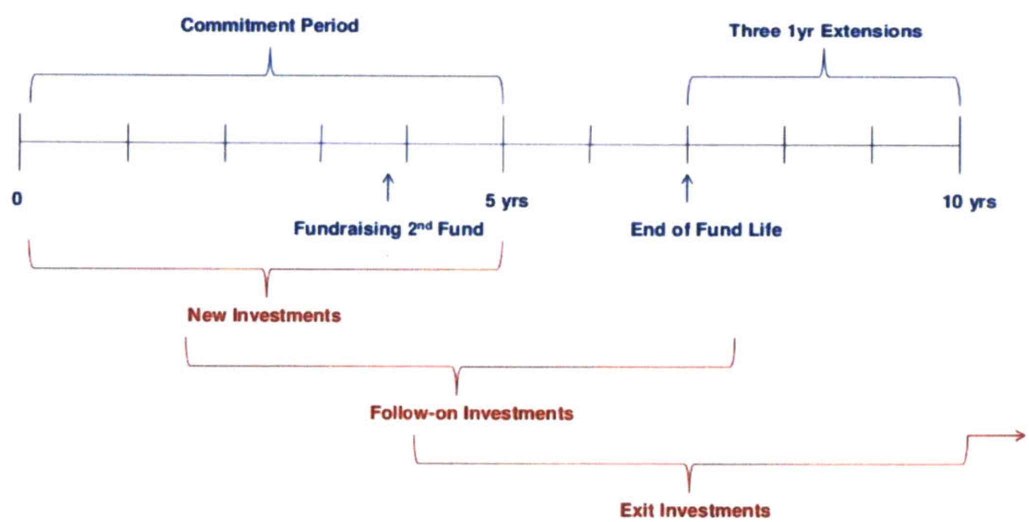

Figure 11: Venture Capital Fund Lifecycle [17]

Chapter 3: State of Artificial intelligence technology

"AI is whatever that hasn't been done yet" - *Larry Tesler* [18]

Artificial intelligence (AI or also termed as machine intelligence) is the science of making machines intelligent agents - able to sense its environment (learn) and take actions (solve) to achieve goals in the world. It is related to using machines or computer programs to understand human intelligence and other biological methods that might not be directly observable. Artificial intelligence emerged as an academic field in 1956, and since then has experienced several waves of successes and failures. AI research has been divided into subfields based on technical considerations - specific goals (machine learning or robotics), use of particular tools (logic or neural networks), philosophical differences - and also based on social factors. Traditionally, we have been aiming to develop a human-like AI system that possess the following capabilities - reasoning, representing knowledge, planning, learning, natural language processing, perception, the ability to move and manipulate objects, social intelligence, creativity, and general intelligence [19]. Various approaches (see figure below) have been formulated to achieve goals - statistical methods, computational intelligence, and symbolic AI.

What are the Artificial intelligence related technologies?

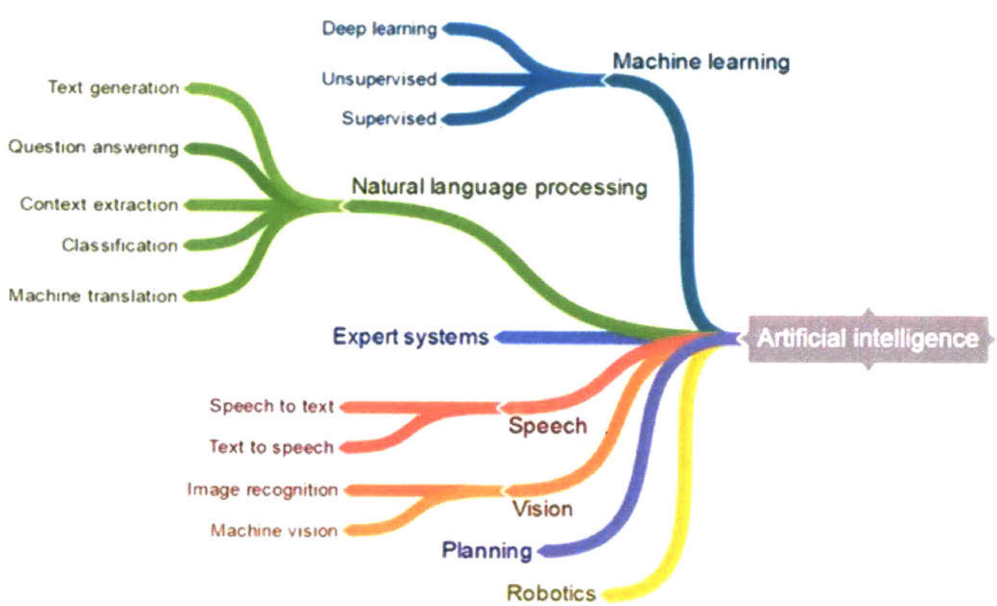

Figure 12: AI Tools and Techniques [20]

Artificial intelligence is being used across many industries - healthcare, automotive, video games, financial services, video games, autonomous vehicles, search engines, online assistants, image recognition, and many more. AI can be applied to any intellectual task. Because of advances in computing power, lower storage costs, large amounts of data, and theoretical understanding, artificial intelligence techniques have become critical elements of digital transformation in the twenty-first century. Some people consider AI a danger to humanity and will result in loss of many jobs, while some say that it will create new jobs as it will eliminate some human jobs.

AI systems today can execute (and in some cases, outperform human performance) many tasks - facial and voice recognition, automatic navigation, synthesizing information, medical diagnostics, recognizing complex patterns, screening resumes and concluding. Amazon has achieved impressive results ("click to ship" cycle time reduced from around 65 minutes to just 15 minutes after its acquisition of robotics company Kiva, yielding a return close to 40% on the original investment) [21]. Netflix is using an algorithm to personalize recommendations to its 100 million global subscribers, avoiding revenue loss of $1B annually because of canceled subscriptions) [22]. However, some of the most prominent success of AI stems from advancements in machine learning algorithms. Historically, human knowledge was codified in computer programs, mapping inputs to outputs by computer programmers. Whereas now, machine learning programs can use categories of general algorithms to identify input-output mapping on their own by feeding large data sets. By using such sophisticated machine learning algorithms, machines have made tremendous growth in the areas of perception and cognition - two essential skills needed for most of the human tasks. For instance, error rates in labeling the photo content on ImageNet, a database of over 10 million image records, have fallen from over 30% in 2010 to 2.2% in 2017 [23]. AlphaGo game has achieved superhuman performance, beating best human players in the Go game by using Deep learning techniques (machine learning technique based on simulation of human neurons via neural nets) along with reinforcement learning. Machine learning, the most powerful tool behind AI, can be applied in different contexts [23]:

(a) *Supervised learning* - This type of learning most heavily explored and common type of machine learning that is being used in the commercial applications. This algorithm involves learning some general function given a set of training examples of input-output pairs. This type of algorithm could be used to classify, f(x) = y, whether an email is a spam or not (binary label y) given an email message as an input (x). Apart from classification, this type of machine learning could be used in prediction - predicting future stock price from historical data, predicting customer purchase behavior, and many more such use-cases.

(b) *Reinforcement learning* - This type of learning involves some agent interacting via a set of actions to learn a strategy for selecting the best sequence of actions to execute an initial stage. For instance, in learning chess game, the algorithm [F(state) = action] would take the current board position (stage) as input and outputs the best strategy or move (action) to win the game. Compare to training function in supervised learning, the training signal is not a direct signal, such as the eventual outcome of the game after sequential actions.

(c) *Unsupervised learning* - This type of learning requires no training labels and usually involves approaches, such as clustering the data or find its critical attributes without a specific, pre-defined function to be learned. For instance, unsupervised learning could be used to cluster customer records into different groups with similar backgrounds to help discover customer segments most interested in the product purchase.

Adoption of Artificial intelligence technology and Decision-making

AI investments are growing at a high rate (companies invested $26B-$39B mainly in AI research and development in 2016), but adoption remains low in 2017 (approximate 1 in 20 companies have successfully incorporated AI technologies in their businesses). AI research is dominated by tech firms such as Google and Baidu. Machine learning technology received the most significant share of external (VC/PE firms spending a total of $6B-$9B) as well as internal investment in 2016 [22]. AI adoption is at an early, experimental stage outside the tech sector. Very few non-tech firms are currently using AI-related technologies in their core businesses or at scale in other activities. It is also because many companies are uncertain of the business case. High-tech, telecom and financial services are some of the leading adopters of AI (see figure below).

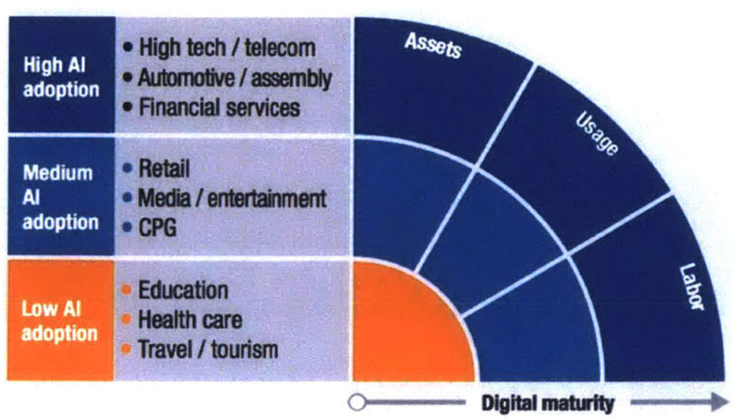

Figure 13: Adoption spectrum of AI across Industries [22]

Investments in these industries are both broad and deep - using AI technologies at the core of their businesses as well as using multiple techniques across different functions. However, there remains a growing gap between early adopters of AI and others. Research studies have shown that firms that combine strong digital capability with aggressive strategies have higher margins and perform better compared to other firms. AI has the potential to optimize and automate business operations, develop targeted marketing strategies, improve forecasting and optimize sourcing, smarter research & development, and enhance user experience. However, it's adoption is not a simple "plug and play" one. A successful AI adoption requires firms to address the following transformation elements:

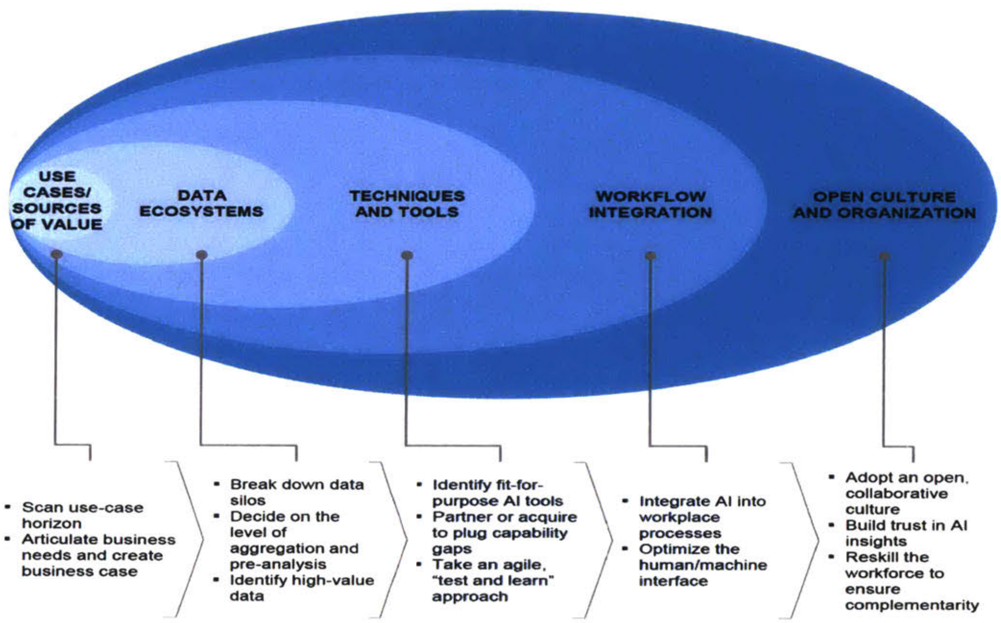

Figure 14: Elements of successful AI Transformation [22]

Investors are betting billions of dollars into AI companies, hoping that AI market will develop quickly and be willing to pay for AI platforms, infrastructure, products, and services. According to PitchBook, only 10 percent of machine learning based startups consider machine learning a core business that generates some revenue [22]. On the other hand, tech giants, such as Amazon, Google, Baidu are investing into AI to improve their business scenarios - optimizing searches, and targeted marketing. In general, traditional companies with some knowledge about AI are still in the experimentation or pilot stage [24]. Very few companies have incorporated AI into their value chain at a large extent [25]. As with any new technology, there are early and late adopters of the technology across sectors. As per McKinsey AI index report [22], there are six features supporting early adoption of AI technology:

1) AI adoption is more in sectors that are already investing at scale in related technologies- cloud services and big data. These sectors are already at the forefront of digital assets and usage.

2) Similar to digital adoption pattern, large companies are investing in AI faster at scale irrespective of sectors compared to small and medium-sized businesses.

3) Early adopters are adopting in one type of AI technology. They incorporate multiple AI tools and techniques to address different business use cases at the same time.

4) Companies that are investing in AI technologies at scale are doing it close to their core businesses.

5) Early adopters are motivated by both upside opportunities of AI and cost savings. AI is also used by companies for product and service innovation apart from the process automation or task automation.

6) Robust AI adoption requires support from executives [25].

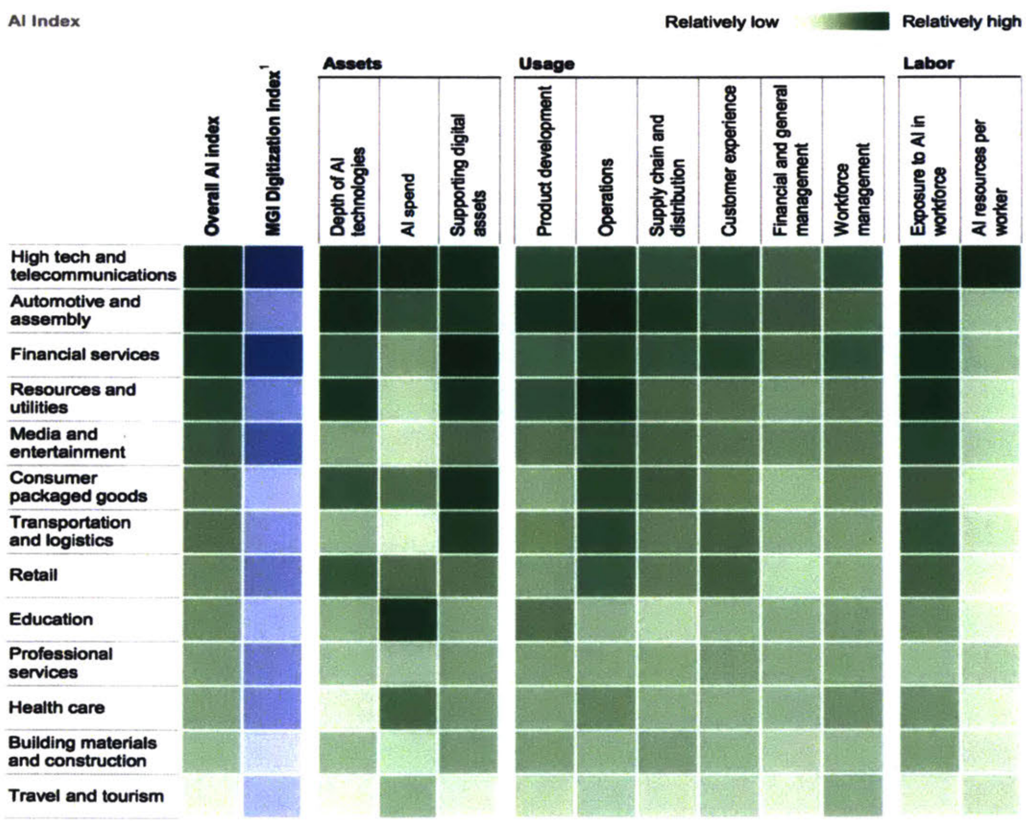

Figure 15: AI adoption index - adoption faster in more digitalized sectors [22]

As we see in the figure above, AI technologies are finding varying degrees of relevance across the value chain. For instance, some functions, such as sales and marketing, operations, and product development, tend to use general AI applications. Whereas, general and finance management lag quite behind. Compared to new digital technology adoption trends that remain on margins away from the core business, AI technologies are getting adopted in areas closer to the core business of a company. Operations, an essential area for financial services, consumer packaged goods sector, and utilities, and customer service, another crucial area for financial services, are both critical areas of AI adoption in the current scenario.

AI technologies are aiding the decision-making process across the value chain in different kinds of businesses today. Any human decision stems out of dissatisfaction between the current state and the desired (futuristic) state of the world. As seen in the figure below, human decisions consist of two broad phases – diagnosis and desirable future state (looking ahead). Diagnosis is the phase of identifying recorded states that are close to the perceived current state of the world. Since decisions involve desired future states, the desires are modeled as preferences (expressed by a utility function) in decision theory. Every decision involves uncertainty of future (subjective probabilities of various outcomes) and granular output. We can then represent futuristic states or outcomes as a function of future events and actions (uncontrolled and uninfluenced by the human subject) attainable from the current state. Based on these futuristic outcomes, the human makes a decision (an action combining possible outcomes with preferences).

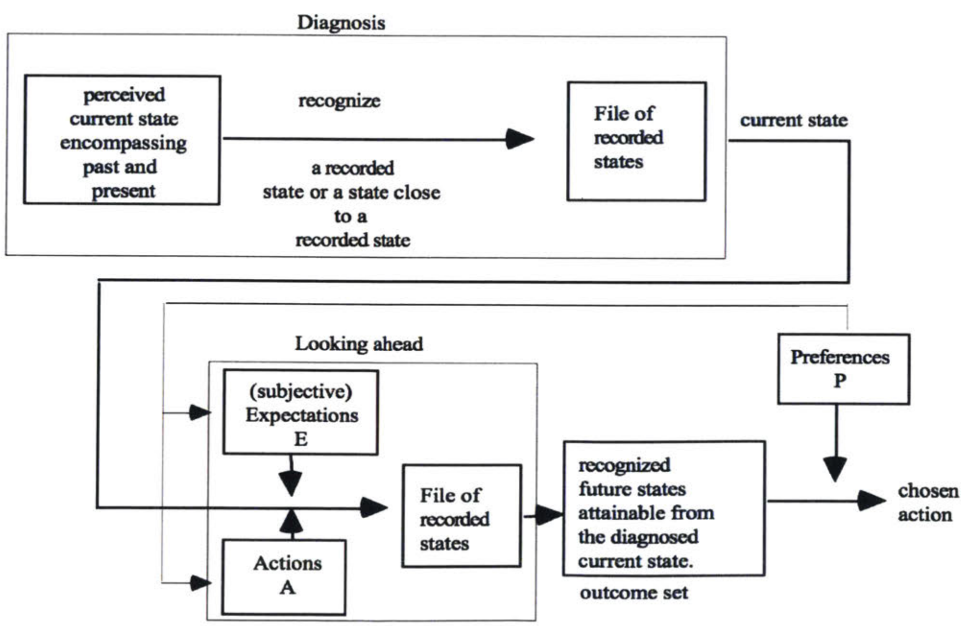

Figure 16: Human decision-making process (based on decision theory) [26]

There are three levels of decision-making capabilities that an AI system can provide: *Assisted Intelligence* (automation of simple tasks), *Augmented Intelligence* (bi-directional value exchange between machines and humans), *Autonomous Intelligence* (AI without the involvement of humans). PwC Strategy& has created a tool called DeNovo (using natural language processing, graph processing, and supervised learning algorithms) that helps evaluate the potential of a new financial technology and also access its utilization [27]. In a similar fashion, an AI system can alert a loan officer of any personal bankruptcy or bad credit risk a customer might previously have and assist the loan officer in the decision-making. Also, AI systems are being used to model the future automobile ecosystem. Intelligent bots are recording the individual decisions made by users, manufacturers, service providers, and other stakeholders in the automobile ecosystem. These AI systems then model customer adoption, business models, advertising, and pricing of car-sharing or of self-driving vehicles. Compared to standard strategy analysis that considers few go-to-market (GTM) scenarios, such AI systems can run more thousands of GTM scenarios to create personalized GTM scenarios in order to maximize revenues [27]. AI simulated algorithms that recommend appropriate treatment procedure to a human doctor after detecting patterns and historical patient records have improved patient outcomes by 50% while reducing healthcare costs by 50% [28]. AI-powered hedge funds are achieving 8.44% annual returns over the last six years, beating human-run decisions.

Building an AI expert system that could mimic or surpass human decision-making is a challenge. Big technology companies are focusing on deep neural networks using millions of data sets to solve problems in classification and perception. We can easily classify the universe, but the gap remains in decision-making. Although deep neural networks can be used for decision making, the problem lies with the availability of large amounts of data sets required to train such systems. Prowler.io, an AI startup based out of Cambridge, is building a decision-making platform using game theory models operating (infer what humans and other AI systems are doing), probabilistic modeling techniques, and reinforcement learning approaches (estimate and account for uncertainty) [29]. The platform is using probabilistic models to generalize to novel situations and to use data to refine strategies in changing environments. Research studies have shown that AI could be used to improve group decision-making in humans by using random learning utility models, combinatorial voting, and Bayesian approaches [30].

How Artificial intelligence is used in Financial services industry?

Financial services industry, comprising of Investment Management, Banking, and Insurance sectors, evolves rapidly and is significantly affected by latest technology and market trends - explosive data growth, new players entering the market, increasing regulatory compliance. AI tools and techniques are being utilized for a wide range of use-cases in the financial services industry. Traditional financial services companies are in the initial stages of using AI technologies in their businesses. There are numerous supply and demand factors that have led to rapid adoption of AI in the financial services industry (see figure below). AI and machine learning tools that are being used in the search engines and self-driving cars can be easily applied in the financial services industry as well [31]. For instance, entity recognition tools that are used in search engines are being used to identify news or social media feed relevant to publicly traded firms. As more and more financial institutions adopt these tools, the incentives to use more sophisticated data to develop more accurate AI and machine learning models may increase [31]. Variety of technological advancements in this sector have led to the creation of required infrastructure and data sets - increase in the availability of high quality market data in structured format (online search trends, viewership patterns) fueled by the growth of electronic trading platforms, use of social media by public traded companies for public announcements, and digitalization of markets facilitating real-time transaction access and direct access. On the demand side, financial institutions are tapping opportunities related to cost reduction, risk management gains, productivity improvements, competitive edge in the market, and regulatory compliance.

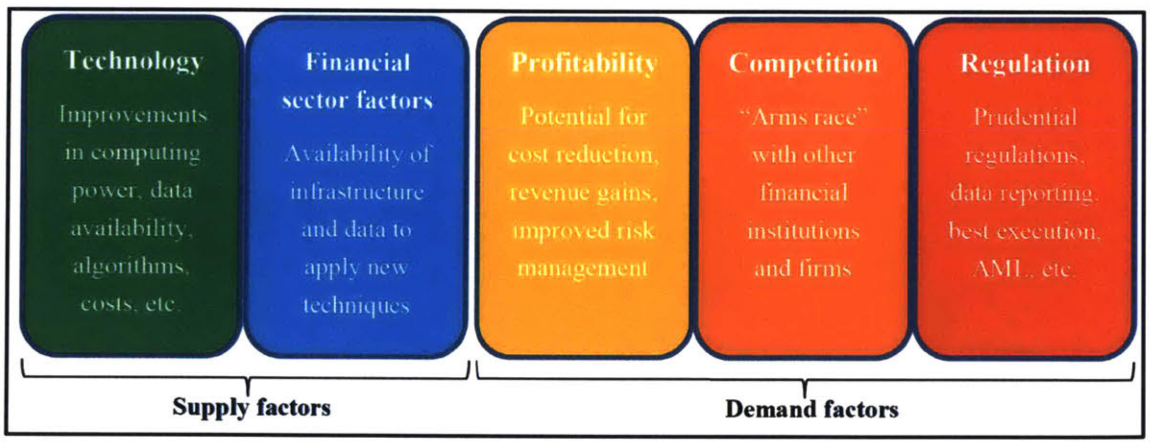

Figure 17: Supply and Demand Factors [32]

AI tools are being adopted for some use-cases in the financial services ecosystem are -

(a) *Customer-focused use-cases*: Financial institutions are using AI tools to improve front-office activities in financial institutions. Machine learning algorithms are being used to access credit quality and fasten lending decisions [32]. These algorithms input historical transaction and payments data, along with data from social media activity, mobile text consumption data, to build segmented customer profile and accordingly access consumption behavior and willingness to pay that would facilitate faster assessment of creditworthiness. Some insurance companies are using vast data sets to identify high-risk cases to reduce claims and improve profitability. Insurance companies are also exploring machine learning to enhance marketing of insurance products by analyzing real-time shopping data or telemetry data from sensors in connected devices, to determine repair costs, to detect and prevent insurable events before they occur. Few companies, such as Kensho Technologies, are also using Natural Language Processing (NLP) techniques to analyze financial reports, past claims to discover critical considerations for human-decision makers. Chatbots or virtual assistants are being used to improve customer service by using sophisticated NLP techniques. Also, Robotic Process Automation (RPA) or logic-driven robots executing set rules and learning from past decisions are being explored to facilitate customer interactions - documentation verification, legal and credit checks [33].

(b) *Operation-focused use-cases*: Financial institutions are also exploring AI tools to improve back-office activities. Banks are using AI and machine learning tools along with mathematical approaches to maximize profits given scare capital (also termed as Capital Optimization) [32]. Few banks have tried to optimize risk-weighted assets (RWA - bank assets weighted based on risk) and have seen 5-10% RWA savings using such machine learning models. Similarly, such tools could also help banks to improve margin valuation adjustment (MVA - determination of funding cost of the initial margin posted for a derivatives transaction) [32]. Banks are also exploring machine learning to understand different kinds of datasets and to simulate the performance of primary models as part of the back-testing process. AI tools are also being applied to bank stress testing for loss scenario analysis. AI tools could also be used to complement market impact models to evaluate the effect of a financial institution's trading on market prices, identify a group of bonds that possess similar behavior, and help determine the timing of trades to minimize market impact.

(c) *Trading-focused use-cases*: Asset managers and trading firms are exploring AI tools to devise trading and investment strategies. For instance, firms are exploring to analyze past trading behavior comprising of large quantities of data to anticipate client' next trading order. Firms are also investigating also to use phone data related to trade execution along with the massive amount of data generated from electronic trading platforms. AI tools can also be used to pro-actively manage risk exposures centrally and alert for warrant intervention for accounts with increased risk profiles. AI tools are also being used to identify signals on price movements over various time periods to efficiently manage a portfolio and generate higher overall returns. In portfolio construction, machine learning is extensively used by quant funds (mostly hedge funds comprising of traders and quants) to create predictive power from data and fully automate investment models [32]. Some firms are utilizing AI tools either in-house or third-party to discover insights from the vast volume of news and publicly available market research.

(d) *Regulatory compliance and supervision related use-cases*: AI tools are being used by regulated institutions for compliance purposes and by regulatory authorities for supervision use-cases. Public sector regulators and supervisors are also utilizing AI tools to enhance efficiency and results of supervision and surveillance. Machine learning and NLP can analyze emails, instant messaging content, documents, metadata to monitor the behavior of traders per the employee surveillance policy for transparency and market conduct. NLP could be used by asset management to interpret new regulations into a common language that could then be used to codify the rules for automation into integrated risk and reporting systems. AI tools are also being explored to know the identity of customers ('know your customer' or KYC process) by using computer vision to identify and compare images in different documents and to calculate customers' risk scores by analyzing data from police records and social media. Machine learning can also be applied to identify systemic risk and risk propagation methods [32]. NLP tools could help authorities to detect and anticipate market volatility, liquidity risks, financial stress, housing prices, and unemployment [31]. In an academic study, models developed using linguistics and mathematical approaches to discover semantics of natural language in US bank disclosures highlighted various market risks. Central banks could also use AI tools for various policy assessments [31]. Some regulators are even using machine learning for fraud detection by identifying complex patterns (evidentiary documents, bank transfers, newspaper articles) and catch suspicious transactions that warrant serious investigation.

Challenges related to Artificial intelligence adoption

As we have seen from examples above, AI has the disruptive potential to boost profits, transform industries, and fundamentally change the society. However, companies are just at an early stage of AI adoption in their businesses although AI is a strategic priority for most of the companies. There are many challenges involving governments, the workforce, and broader society to scale the AI adoption across sectors. Industries that have been successful in integrating and adopting new technologies and managing data might face challenges in adopting AI in their businesses. Leaders don't want to just adopt AI tools because of touted benefits and industry trends; they want to link AI technologies to a specific business problem. While data analytics is being utilized by nearly half of the organizations globally, many companies are still struggling to become a data-driven organization, which is a crucial element of successful AI adoption.

A study conducted by MIT and Boston Consulting Group (see figure below) shows what different organizations consider significant barriers to AI adoption [34]. The study segments the respondents into four different maturity segments: Pioneers (organizations that understand and have adopted AI), Investigators (organizations that understand AI but are not deploying it beyond the pilot stage), Experimenters (organizations that are experimenting AI without deep understanding of the technology), and Passives (organizations that don't understand and are not adopting AI).

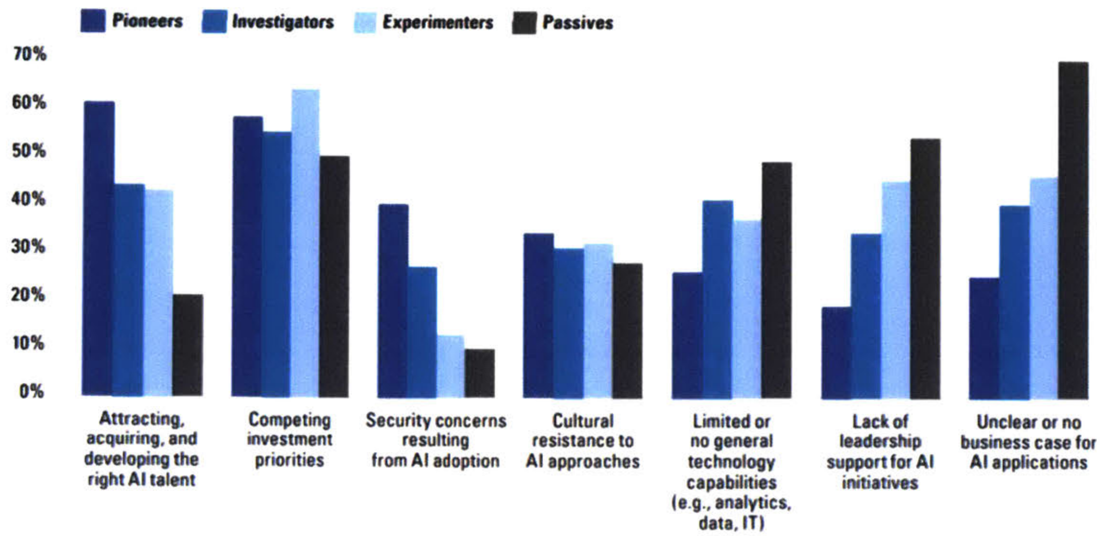

Figure 18: Barriers to AI Adoption [34]

As per the study results, it is evident that the following are the main challenges in AI adoption across organizations from different sectors - misunderstandings about what could be used data for AI tools, make vs buy decisions (hiring skilled talent vs using third-party platforms or services), privacy and regulatory issues regarding data use and compliance adherence, developing an intuitive understanding of AI, organizational flexibility to adapt AI, and strategizing competitive landscape. To maximize AI returns, organizations would need to "re-discover" how AI will disrupt various part of their businesses and how to create a sustainable competitive strategy.

Chapter 4: Analysis

In order to discover opportunities and risks associated with the use of AI tools and techniques in Venture Capital industry, the author analyzes decision-making in eight value chain areas in venture capital - deal sourcing, deal selection, valuation, exits, deal structure, post-investment value-added, internal organization of VC firm, external organization of VC firm. After breaking down the decision-making process, the author has assessed suitability of major AI tools and techniques (Machine learning, Natural Language Processing, Speech, Vision, Video analysis technologies) using a comprehensive 21-item rubric (see appendix) for decision-making tasks in all the eight value chain areas and scored (1 or 3 or 5 values) AI automation feasibility on a range of 21-105 values [23].

Trends in Venture Capital industry

Over the past several years, VC ecosystem has transformed into a barbell structure, with few large mega funds on one side and many small funds on the other along with few moderate-sized funds in the middle [35]. Unicorns (companies with $1B+ valuation) are being pursued aggressively. Instead of supporting viable problems that entrepreneurs are passionate about, VCs tend to chase unrealistic 10x returns at all costs that might lead to some bad decisions and failed products that otherwise could have simple sustainable businesses. Juicero, a cloud-based juice startup, is a perfect example of this. VC firms are encouraging diversity - staffing their teams, building investment thesis. VC firms, such as The Catalyst Fund, Flybridge Partners, are committed to supporting minority-run startup companies. Unshackled VC is focused on investing in immigration-led startup companies. VC firms are building product and design expertise in-house to support and pivot of portfolio companies. Kleiner Perkins Caufield & Byers has created product, design, and technology fellows program to match talent with their portfolio companies. Additionally, VC funds are becoming more focused on theme investing (vertical investing) as tech industry becomes more pervasive. The Collaborative Fund support companies that are solving problems to improve cities and the lives of children (supporting a higher purpose). Whereas, The Yield Club is solely focusing on agricultural technology (supporting complex industries) [36]. Creation of many small, highly-focused funds creates an ecosystem for vetting of upcoming and frontier technology solutions which often require relatively small funds and are otherwise difficult to assess.

In the past few years, VC firms are growing globally, targeting other markets in south-east Asia, middle-east, Africa [37]. With the proliferation of new platforms, such as AngelList, Gust, and many more, investors now have more choice in selecting and investing great companies. With investors' pool of money growing year after year, it is becoming relatively easy for startup companies to reach, pitch, and raise capital from VCs.

Risk-Reward relationship

In order to better understand the decision-making process of VCs, it is important to understand one of the key drivers of their decision-making process ("Go" or "No Go" decisions): The Risk-Reward assessment. Venture capital is a high-risk and high-reward asset class. No investment opportunity is a risk-free or a low risk. Every investment opportunity involves various risk and reward characteristics (see figure below that describes the risk-reward relationship in reference synthetic bio industry) [29]:

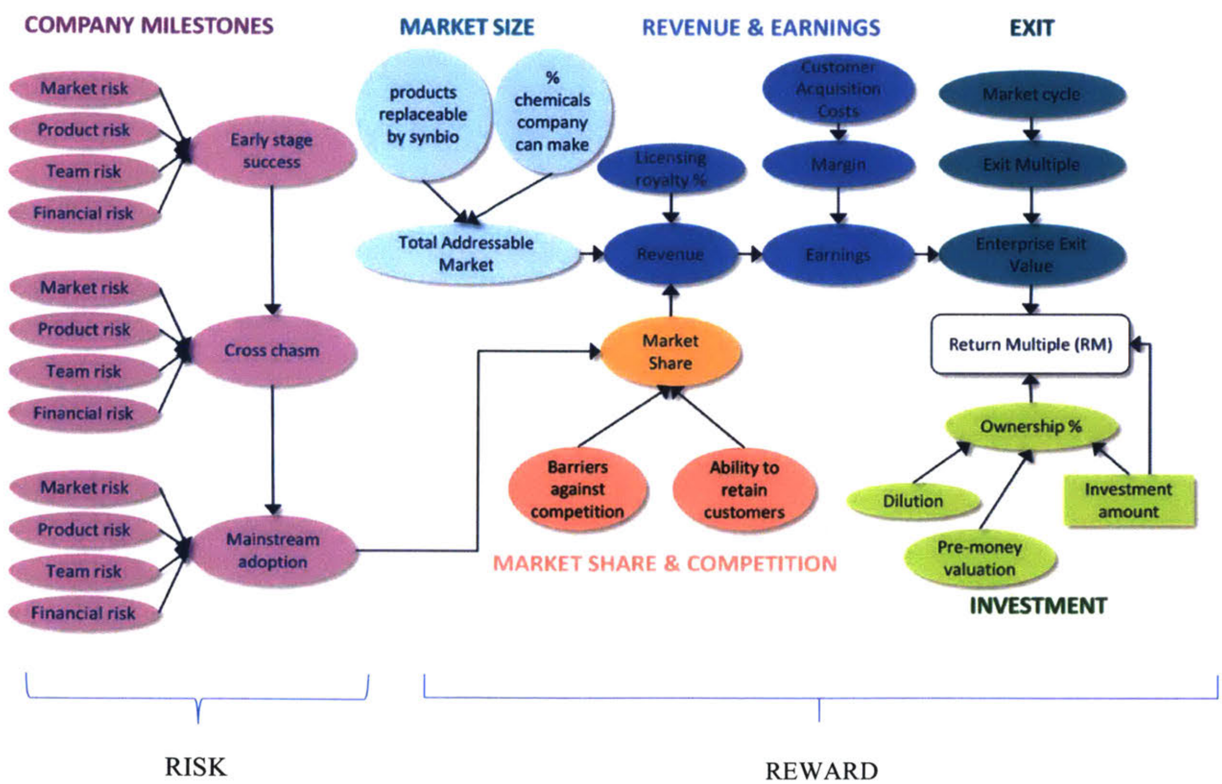

Figure 19: Risk and Reward Relationship Model [38]

As we see in the above figure, main risk factors across different stages of a company include effects of competition, team risk, ability to scale operations, capture and sustain market share, and others. Some risks might also originate from investor's own decision-making process (assumptions, cognitive biases, decision mechanics). Reward factors include market factors (market share and size), and financial factors (valuation model, investments or debts, prior shares, future dilution, exit scenarios).

Risk-Reward relationship various across funding stages. Later stage funding rounds have a lower risk compared to early stage. A startup company's risk decreases as the company grows. The total risk of failure in a company is compounded risk involving every future and current round's risk. While earlier rounds carry more risks, there is also an opportunity for higher returns to balance the risk. Estimated returns on investments in every round (see figure below) suggest that sweet spot for investing comes in the Series A and Series B stage investment. Risk-Reward assessment across funding rounds greatly influences VCs investment decisions as to whether and how to invest in a startup company.

Figure 20: Risk adjusted Returns across stages [39]

Decision-making process breakdown

This section describes the primary outcome of the main activities involved in the eight value chain areas of a venture capital firm and how overall decision-making happens in that value chain area based on the analysis from venture capital process break down in Chapter 2:

(a) *Deal Sourcing*: The primary outcome of deal sourcing (also known as deal flow) process is to generate numerous high-quality potential investment opportunities that align with the investment thesis of the venture fund. VCs want to funnel down potential deals to a small number of investable opportunities. The primary outcome of this decision process depends on the sources from where investment opportunities should come from and the deal sorting mechanism used during the deal flow funnel. The most valuable deals come from referrals from entrepreneurs or companies in which the fund has previously invested, other venture capitalists looking for syndicate opportunities, and professionals in the VC network who are aware of fund's investment focus [8]. At each stage in the deal flow process, a chunk of opportunities is eliminated depending on the fund's selection criteria. Traditionally, partners or associates engage with their professional network (warm introductions over an in-person meeting, email, phone conversation, cold-calls) or entrepreneurs in conferences and events to discover potential opportunities. A deal that is generated either inbound by the firms' resources or outbound by a professional network is first considered by the individual originator who could be a partner or an associate. If the deal shows potential from this initial assessment, then a member of the venture capital firm meets the management of the sourced company at least once. If the member finds the opportunity still attractive, the opportunity is then evaluated by partners at the venture capital firm. After this approval from the partners, the opportunity is then discussed and evaluated (exercised due diligence, offered term sheet) by the investment committee at the venture capital firm.

(b) *Deal Selection:* The primary outcome of deal selection decision process is to screen and select deals in order to construct an optimum portfolio. Different venture funds have different selection criteria at different stages (initial screening, first meeting, second meeting, due diligence process) of the deal funnel process. VCs consider several factors in their investment decisions - management team, entrepreneur's personality and background, product or service, market characteristics, financial characteristics, evidence of customer interest or user traction, flexibility in technology and strategy, stage of the business, potential exits and return on investment, syndicate investors, fund fitment. Factors, such as financials and potential customers are decisive in nature, whereas other factors, such as quality of management team, barriers to entry, and business potential related are more predictive of venture success. VCs use different types of interaction mechanisms to gather this information from the entrepreneur - interviews, questionnaire, surveys, verbal protocol. Entrepreneurs also supply information in various digital forms - executive summary, business plan, investor slide deck (short and long pitches), backup slides for answering more questions, financial model, investor control schedule, product/service demo or video reel.

(c) *Valuations:* The primary outcome of valuations is to estimate the value of the company at the time of exit and potentially analyze VCs stake in the company. VCs use various tools and methods to value companies. CFOs of large companies mainly use discounted cash flow (DCF) analysis, where Private Equity (PE) investors generally use Internal Rate of Returns (IRR) or multiple of invested capital analysis to value investments. VCs might several financial metrics, such as IRR, cash-on-cash return, or Net Present Value (NPV) for forecasting cash flows. VCs use appropriate valuation method to value companies (see figure below):

	Valuation Method	Principle
1	Berkus	Valuation based on the assessement of 5 key success factors
2	Risk Factor Summation	Valuation based on a base value adjusted for 12 standard risk factors
3	Scorecard	Valuation based on a weighted average value adjusted for a similar company
4	Comparable Transactions	Valuation based on a rule of three with a KPI from a similar company
5	Book Value	Valuation based on the tangible assets of the company
6	Liquidation Value	Valuation based on the scrap value of the tangible assets
7	Discounted Cash Flow	Valuation based on the sum of all future cash flows generated
8	First Chicago	Valuation based on the weighted average of 3 valuation scenarios
9	Venture Capital	Valuation based on the ROI exepected by the investor

Figure 21: Valuation Methods [40]

(d) *Deal-structure:* The primary outcome of deal structuring is sophisticated structuring and contracting of their investments, basically defining ownership, in order to ensure that the entrepreneur is greatly compensated if he or she performs well and that the investors can take control if the entrepreneur fails to perform. VCs achieve these by properly allocating cash flow rights that govern upside equity, control rights that allow the VCs to intervene in case entrepreneur is not performing well, liquidation rights that gives senior payoff to VCs in case entrepreneur is not performing well, and employment terms that governs the vesting incentives and motivations for the entrepreneur to perform and stay with the firm. VCs contracts revolve around these risks - internal risk, external risk, and risk of execution. Another important element of deal structuring is investment syndication with other VCs. A deal structure consists of many terms that define the overall deal structure. The deal terms are a function of many factors - investor type (institutional or angel), size of investor's checkbook, the economics of investment opportunity, funding cycle. Major deal terms in a deal structure are preferred return, protection of and position future money, management of the investment, exit strategies. These deal terms, once defined by the VC initially, are then actively negotiated between the VC and the entrepreneur to right define the deal terms that are in the best interests of the VC and the entrepreneur.

(e) *Post-investment value-added:* The primary outcome of post-investment value-added is to monitor, support, and govern portfolio companies. It could often mean to replace entrepreneurs if they are not performing well. VCs provide significant help in hiring outside managers and executive directors. These attributes can be classified as different forms of capital beyond monetary sense: intellectual capital (utilizing their knowledge and expertise) and relationship capital (utilizing their professional network) [41]. Many VCs have relevant industry experience that helps a portfolio company (especially an early-stage company) avoid any pitfalls. VCs also help identify key business partners or customers or other venture capitalists who would be good candidates to build relationships with the portfolio companies.

(f) *Exits:* The primary outcome of exit decisions is to generate potential returns from a portfolio company. VCs play an important role in successful exits (sale of the shares) and exit strategies (if the company does not perform well) of portfolio companies as exit decision is equally important as selection decision. It is often considered an important metric to evaluate the performance of a VC especially by LPs for follow-on investing in a VC fund. Exit decisions have two main dimensions: exit route, and the optimal timing of the exit. Most common successful exit options for VCs are IPO and M&A. VCs desires to retain exit as well as liquidity options by negotiating several control rights (such as registration right, drag-along right, tag-along right, call and put options, and more than power the VC to intervene when necessary and secure his or her interests) in the financial contracts or deal structure [42]. VCs time their exits by appropriately staging their financing in several rounds. Another factor that influences the exit decisions are the characteristics of product market related to the portfolio company.

(g) *Internal organization of a VC firm*: The primary outcome of an internal organization structure of a VC firm (employees, skills, time devoted by employees/partners to particular tasks) is to yield better performance. There is a strong positive relationship between the degree of specialization by an individual VC and the firm success. Investment focus of a VC firm affects decision-making and overall performance of the VC firm. As we have seen before, VC firms could be categorized as a generalist or a specialist. Generalist VC firms tend to underperform compared to specialist firms. Generalist VC firms do not tend to effectively allocate capital across industries and might underperform within a particular industry. However, there is not much difference in the performance of specialist or generalist VC firms if the VCs in the firm are specialists. Thus, internal structure (number and types of employees in a VC firm), their specialization areas, nature of daily tasks, group decision-making all affect the performance of a VC firm.

(g) *External organization of a VC firm*: External organization of a VC firm mainly involves the relationship between investors (LPs) and VCs. As we have seen before, VC managers have various implicit and explicit incentives to perform well. Different incentives for investors and for VCs and the alignment of incentives between investors and LPs drive decision-making, overall fund performance, fund persistence, market return expectations, and follow-on investing decisions.

Feasibility analysis

The feasibility analysis is the process of analyzing suitability of AI automation of overall decision-making scenarios in eight value chain areas of a venture capital firm. The feasibility analysis of a core area is calculated at an aggregate level (considering the primary outcome of the key decision-making task in that core area) representing the feasibility of AI automation of all sub decision-making scenarios in that value chain area. The scoring and judgments of each value chain area are based on author's knowledge of decision-making tasks involved in that value chain area and the rubric criteria to score the rubric items.

For instance, the author uses the following criteria to score the following rubric item from the list of 21 items (see appendix) to access decision-making involved in buying a home. The primary outcome of buying a home is to select and finalize the best home based on an individual's preferences and other selection criteria (financial, geographical, and more). The scoring criteria for all rubric items specifies lower, middle, and upper bound selection criteria. The first step before scoring any rubric item is to analyze all the possible inputs (current state) and outputs (futuristic states) along with their form structure involved in a particular decision-making task by further breaking down the decision-making process. The next step is to gather as many as possible quantitative data points or general facts that define relationship between input and output parameters. Then for each rubric item, access the selection criteria of that item based on the gathered knowledge and accordingly assign the best possible score.

Example 1- [Rubric Item] *The task output is error tolerant*

1: A mistake could lead to serious harm, injury, or death to those involved, or could lead to lasting negative consequences (e.g. mistake during surgery, mistake at a nuclear facility)

3: A mistake will have negative consequences, but can fixed with some work (e.g. a construction mistake, or human resources slip-up will be noticed and reprimanded, but would not result in termination of employment or injury)

5: A mistake can be easily fixed, and holds few, if any negative consequences (e.g. a slip up in factory work or mail sorting mistakes could go potentially unnoticed)

In the case at hand, the author would score buying a home decision-making for rubric item as 2 since a mistake could potentially lead to financial loss or uncomfortable living standards for some time, but there are couple of ways to fix the mistake (law suit, sell the current house at some loss and buy another desired house). The other closest option in this case would be 3, but since negative consequences are quite high in this case, the best option would be 2.

Example 2 - [Rubric Item] *Task does not require detailed, wide-ranging conversational interaction with a customer or other person*

1: Task requires explaining something deeply to another person, or having a deep conversation that cannot be predicted in advance (e.g. therapy, negotiation)

3: Task involves communicating but about a relatively small, pre-set range of topics (e.g. giving instructions or directions, answering/asking specific/common questions)

5: Task doesn't require any form of communication/conversation with another person (e.g. solving equations, lifting objects, observing)

In the case at hand, the author would score buying a home decision-making for rubric item as 1 since buying a home requires heavy negotiation between buyer and seller of the home. Similarly, the author follows the same judging and selection criteria to score different rubric items for decision-making in venture capital.

To strengthen scorings and judgments of each rubric item, the author has analyzed quantitative data points that provide more information on how decisions are made in that value chain area. The quantitative data points are analyzed from the survey results of 681 venture capital firms conducted by other academic researchers [10] that details how VCs make decisions in a particular functioning area as well as analyzed from the general literature review.

(a) *Deal Sourcing:* VC firms use these primary sources to source potential deals (approximate % of deals closed per source; varies depending whether a VC firm is early-stage or late-stage) - professional network (31%), proactively self-generated (28%), referred by other investors (20%), inbound from management (10%), referred by portfolio company (8%), quantitative sourcing (2%). A VC spends on an average 15.2 hours per week on deal sourcing activities. Research studies suggest that a wide-funnel of deal origin and deal selection are important drivers of returns. Studies have also show that high performing VC are more likely to invest in highly successful serial entrepreneurs. Many VC firms are also using a quantitative approach to deal sourcing by mining rich data from platforms and services, such as AngelList, Gust, SEC filings and more, to identify opportunities that would yield high returns. A median VC firm closes about 4 deals per year after considering about 400 sourced opportunities [10]. One in four opportunities led to meeting the management, one-third of those are reviewed by the partners, half of the opportunities reviewed at a partner meeting proceed to the due-diligence stage, one-third of those opportunities are offered a term sheet.

Item	Score	Comments
Input-Output information explicitly specified in machine-readable format	3	Opportunity details, investment thesis criteria, and deal quality (rank) information can be specified.
Information recorded or recordable by computer	3	Opportunity information, investment thesis, deal quality can be recorded
Task does not require a wide range of complex outputs	3	Ranking a deal requires some key perspectives from referrals and partners
Task feedback is available through plentiful historical data	1	Accessing the real value of a deal might takes 7-10 years
Output is error tolerant	1	Not sourcing a high-quality does not pose any major negative consequences
Not important that outputs are perceived to come from a human	1	Deal sourcing is heavily based on human referrals
Task does not require complex, abstract reasoning	3	Deal sourcing requires some initial-level screening and reasoning
Task is mainly concerned with matching information to concepts, predictions, or actions	1	Some deals can have clear input-output mapping, whereas deals referred by humans might not
Task does not require detailed, wide-ranging conversational interaction with a customer or another person	3	Deal sourcing involves pre-set human conversations in order to access a deal
Task is highly routine and repeated frequently	3	Deal sourcing is fairly routine but can be done in different ways each time
Task is describable with rules	3	Deal sourcing might have some general rules to access the quality of a deal
No need to explain decisions during task execution	3	Deal sorting requires explanation of screening decisions to filter deals
Task can be converted to answering multiple choice questions, ranking options, predicting a number, or grouping similar objects	5	Deal sourcing involves predictions, sorting and filtering of deal options
Long term planning is not required to successfully complete the task	1	Deal sourcing involves planning a timeline of several months
Task might require working with text data	5	Deal sourcing involves reading introductory emails, reading executive summary, marketing content
Task might require working with image/video data	3	Deal sourcing might involve creating marketing content, analyzing video introductions or executive summaries
Task might require working with speech data	3	Deal sourcing involves moderate communication, listening and talking activities

Task might require working with other types of digital data	3	Deal sourcing involves analyzing market trends, company financials (excel).
Many components of the task can be completed in a second or less	3	Component tasks of deal sourcing does not take long time to complete
Each instance of the task is similar to other instances in terms of executions; Actions can be measured	5	Data regarding opportunity details can be made available and the output (deal quality) can be measured
Actions in the task must be completed in a very specific order, and practicing the task to get better is easy	5	Deal funnel involves sequential actions that could be practiced many times to yield better high quality deals
Total	**61**	

Table 1: Deal Sourcing Analysis

(b) *Deal Selection:* VC firms have different criteria to select investments. Some firms consider the management team more important while others consider business (product, technology, competition, business model) more important while selecting investments. In most-cases, VCs consider management team an important selection criteria (especially for early-stage companies). Qualities, such as ability, industry experience, are considered most important in a management team. Passion, entrepreneurial experience, teamwork qualities in a management team are considered of some importance. Business-related criteria are also considered important especially for late-stage companies (business model, product, market, industry in decreasing order of priority). Fit with the fund's investment focus is considered of some importance by a VC firm. Valuation and post-investment value-added factors are considered of some importance by a VC firm. VCs spend substantial resources to conduct due diligence on their investments - average deal-closure time is 83 days, average firm spends around 118 hours on due diligence and calls for around 10 references.

Item	Score	Comments
Input-Output information explicitly specified in machine-readable format	3	Company details, selection criteria, and predicted company success/survival can be specified.
Information recorded or recordable by computer	3	Management/Business details of a company, selection criteria can be recorded
Task does not require a wide range of complex outputs	3	Deal selection requires moderate level of interacting with different stakeholders
Task feedback is available through plentiful historical data	1	Accessing the return of portfolio investments might take about 10 years
Output is error tolerant	1	Bad portfolio construction or deal selection leads to negative returns

Not important that outputs are perceived to come from a human	3	Deal selection or portfolio construction can be a quantitative and outcome is usually predictive in nature
Task does not require complex, abstract reasoning	3	Deal selection requires some reasoning but can be broken down into rules
Task is mainly concerned with matching information to concepts, predictions, or actions	5	Statistically, deal selection has clear mapped inputs - output parameters
Task does not require detailed, wide-ranging conversational interaction with a customer or another person	3	Deal selection might involve communication about pre-set range of topics (due diligence stage, communicating with entrepreneur)
Task is highly routine and repeated frequently	5	Deal selection is fairly routine and most of the times carried out in the same manner
Task is describable with rules	5	Deal selection can be defined with set of rules to access set of companies
No need to explain decisions during task execution	3	Deal selection involves some communication of decisions in order to gain consensus from other partners
Task can be converted to answering multiple choice questions, ranking options, predicting a number, or grouping similar objects	5	Deal selection involves assessment, predictions, and selection of right companies
Long term planning is not required to successfully complete the task	1	Deal selection involves planning a timeline of several months
Task might require working with text data	5	Deal selection involves reading business plans, pitches, investor deck, questionnaire, other supporting documents
Task might require working with image/video data	5	Deal selection involves analyzing entrepreneur's pitches, product demos
Task might require working with speech data	5	Deal selection involves series of interviews with entrepreneurs
Task might require working with other types of digital data	3	Deal sourcing involves analyzing market trends, company financials, and more.
Many components of the task can be completed in a second or less	3	Component tasks of deal selection does not take long time to complete
Each instance of the task is similar to other instances in terms of executions; Actions can be measured	5	Data regarding company/founder details can be made available and the output (success/failure of the company) can be measured
Actions in the task must be completed in a very specific order, and practicing the task to get better is easy	5	Deal selection involves sequential actions that could be practiced many times to yield better portfolio construction
Total	**75**	

Table 2: Deal Selection Analysis

(c) *Valuation:* The most popular financial metrics that VCs use are cash-on-cash multiples (multiple of invested capital; average expected multiple of 5) and IRR (average expected return of 31%). The next common financial metric used are NPV methods. Different investments face different kinds of risks. Few VCs account for systemic risk and neglect market risk while computing their target returns. Early-stage investors sometimes don't use any financial metric and often make gut based investment decisions. Very few VCs quantitatively analyze past investments decisions and performance. Roughly half of VCs account for time to liquidity in making an investment decision. VC firms as an investment class make investment decisions in a manner that is inconsistent with general predictions and recommendations of finance theory. Some VC firms (especially late-stage) forecast cash flows for a period of 3 to 4 years. About a third of portfolio companies (mainly late-stage) meet projections. Portfolio companies, with valuations of over $1 billion (unicorns), are most overvalued.

Item	Score	Comments
Input-Output information explicitly specified in machine-readable format	3	Possible to represent input/output (cash flows, investment decision, performance, dollar value) information in some cases
Information recorded or recordable by computer	3	Past investments decisions, performance, projected cash flows, comparable company information can be recorded
Task does not require a wide range of complex outputs	3	Valuation might require insights from VC experience for early-stage companies
Task feedback is available through plentiful historical data	1	Accessing the real value of a company might require several years
Output is error tolerant	3	Valuations are always tricky and mainly act as a proxy for analyzing VC share
Not important that outputs are perceived to come from a human	5	Valuations are computational in nature
Task does not require complex, abstract reasoning	3	Valuation requires some reasoning in choosing financial metric and accessing market beta and tax shields
Task is mainly concerned with matching information to concepts, predictions, or actions	3	Valuation has defined inputs and outputs and usually involves predicting the value based on several chosen inputs
Task does not require detailed, wide-ranging conversational interaction with a customer or another person	3	Valuation might require communication with humans to gather input information especially for early-stage companies
Task is highly routine and repeated frequently	3	Valuation is fairly routine but can be done in different ways each time

Task is describable with rules	3	Valuation has some general rules applicable to estimate value of all types of companies
No need to explain decisions during task execution	5	Valuation is only concerned with computing the output given all the input information
Task can be converted to answering multiple choice questions, ranking options, predicting a number, or grouping similar objects	5	Valuation involves estimating and predicting the value of a company
Long term planning is not required to successfully complete the task	3	Valuation can be done within few weeks/days
Task might require working with text data	5	Valuation involves reading market sentiment reports (beta and discount rates)
Task might require working with image/video data	3	Valuation might involve analyzing market analyst videos
Task might require working with speech data	1	Valuation does not involve working with speech data
Task might require working with other types of digital data	1	Valuation does not involve analyzing other types of digital data
Many components of the task can be completed in a second or less	3	Component tasks of valuation does not take long time to complete
Each instance of the task is similar to other instances in terms of executions; Actions can be measured	3	Input data can be collected as well as estimated and output data can vary depending on varied input assumptions
Actions in the task must be completed in a very specific order, and practicing the task to get better is easy	5	Valuation involves sequential actions that could be practiced many times to yield better estimations
Total	**67**	

Table 3: Valuation Analysis

(d) Deal Structure: Deal structure usually consists of some investor-friendly terms, some entrepreneur/founder-friendly terms, and some neutral terms. Pro-rata rights (which give investors right to perform in the next round of funding) is used in mostly all deal structures. Participation rights that give VCs power to combine upside and downside protection are used in roughly half of the investment structures. Redemption rights with which VCs possess the right to redeem their investment or demand from the company the repayment of original amount is granted in almost half of the cases. Other investor-friendly terms (cumulative dividends accumulation over time, full-ratchet anti-dilution protection, liquidation preference) are not used much often in investments. In general, VCs are not very flexible on most of their terms. The least negotiable terms for VCs (includes terms that manage internal risk) are pro-rata rights, anti-dilution protection, liquidation preference, valuation, board control, and vesting, whereas VCs are most flexible with dividends, redemption rights, participation, option pool, and investment amount. VC firms (especially early-stage) syndicate with other investors in almost more than half of investment deals. Complimentary expertise, risk sharing, and capital constraints are some important factors that VCs use in syndicate decisions. Professional networks play a key role in selecting right syndicates who bring new skills to the investment team. Expertise, past shared success, reputation, track record, capital are some important factors that VCs use to select syndicate partners.

Item	Score	Comments
Input-Output information explicitly specified in machine-readable format	1	Very difficult to specify investor's preferences, entrepreneur's preferences and historical deal terms and structures
Information recorded or recordable by computer	3	Negotiations, deal contracts, outcomes can be recorded (video, text)
Task does not require a wide range of complex outputs	1	Deal structuring involves active negotiations that could yield many complex outputs
Task feedback is available through plentiful historical data	1	Accessing the real value of optimal deal structure takes 7-10 years
Output is error tolerant	1	Defining lose deal terms greatly impacts the performance of entrepreneur and eventual success of the company
Not important that outputs are perceived to come from a human	1	Final deal structure is heavily based on human negotiations
Task does not require complex, abstract reasoning	1	Deal structuring requires complex reasoning in selecting and defining right deal terms
Task is mainly concerned with matching information to concepts, predictions, or actions	1	Inconsistent input-output variables in different deal structures
Task does not require detailed, wide-ranging conversational interaction with a customer or another person	1	Deal structuring involves active negotiations between VC and entrepreneur
Task is highly routine and repeated frequently	3	Deal structuring is fairly routine but can be done in different ways each time
Task is describable with rules	3	Deal structuring might have some rules to access and define right deal terms
No need to explain decisions during task execution	1	Deal structuring requires explanation of selecting and defining deal terms
Task can be converted to answering multiple choice questions, ranking options, predicting a number, or grouping similar objects	3	Deal structuring involves predictions, sorting and filtering of deal terms and also to select syndicates
Long term planning is not required to successfully complete the task	1	Deal structuring involves planning a timeline of several years

Task might require working with text data	5	Deal structuring involves reading many documents - business plans, reports, pitch decks, emails, and more.
Task might require working with image/video data	3	Deal structuring might involve negotiations online (captured using video).
Task might require working with speech data	5	Deal structuring involves heavy communication activities between VC and entrepreneur
Task might require working with other types of digital data	1	Deal structuring doesn't involve working with other types of digital data
Many components of the task can be completed in a second or less	1	Component tasks of deal structuring take long time to complete
Each instance of the task is similar to other instances in terms of executions; Actions can be measured	1	Each instance of deal structuring decisions is unique and is difficult to measure
Actions in the task must be completed in a very specific order, and practicing the task to get better is easy	1	Deal structuring involves active negotiations that are unique and hard to predict
Total	**39**	

Table 4: Deal Structure Analysis

(e) *Post-investment value-added:* Roughly around half of VCs interact with their portfolio companies at least once in a week and most of the VCs interact with their portfolio companies more than once per month. Most of the VCs are also involved to provide strategic guidance to their portfolio companies by acting as board members or board observers. Around 72% of VCs help their portfolio companies connect with other investors for future rounds. Around 70% of VCs help companies connect with customers and also provide operational guidance. Roughly around half the VCs help in hiring board members and employees. Few VCs also support liquidity events (introducing a company to potential acquirers or investment banks for M&A), mentoring, product development (help with expansion, advice, operating procedures), and various board service activities (such as board governance).

Item	**Score**	**Comments**
Input-Output information explicitly specified in machine-readable format	3	Hiring potential employees or board members, professional network to help connect customers could be specified
Information recorded or recordable by computer	3	Potential recruits, customers, investors information can be recorded

Task does not require a wide range of complex outputs	3	Value-added mainly involves suggestions, guidance. Some cases, might involve planning and difficult actions
Task feedback is available through plentiful historical data	3	Feedback can be received in short time span for some scenarios
Output is error tolerant	3	Negative outcome of value-added services can be fixed with some work
Not important that outputs are perceived to come from a human	3	Some value-add services could be provided by non-human, others require human connection (difficult actions)
Task does not require complex, abstract reasoning	3	Some services require complex reasoning, whereas others can be defined via rules
Task is mainly concerned with matching information to concepts, predictions, or actions	3	Some services involve defined inputs and outputs, whereas hard to define for some services
Task does not require detailed, wide-ranging conversational interaction with a customer or another person	3	Mentoring, Guidance requires human interaction; Hiring/Connecting does not.
Task is highly routine and repeated frequently	3	Value-add services are fairly routine but can be done in different ways each time
Task is describable with rules	3	Value-add services might have some general rules (hiring, connecting, mentoring, monitoring, board activities)
No need to explain decisions during task execution	3	There is some need to explain decisions (especially for difficult actions)
Task can be converted to answering multiple choice questions, ranking options, predicting a number, or grouping similar objects	3	Some services (hiring, connecting, monitoring) involves matching, predicting, while others might not
Long term planning is not required to successfully complete the task	3	Value-add services are mostly concerned with a timeline in the range of months
Task might require working with text data	3	Value-add services might require some reading (market trends, monitoring reports)
Task might require working with image/video data	3	Value-add services might involve product demo videos to connect with customers
Task might require working with speech data	5	Value-add services involve heavy conversation between VC and entrepreneur or prospective executive candidates
Task might require working with other types of digital data	1	Value-add services do not require working with other types of digital data
Many components of the task can be completed in a second or less	3	Component tasks of value-added services does not take long time to complete

Each instance of the task is similar to other instances in terms of executions; Actions can be measured	3	Different outcomes of value-added services can be captured and might be similar to other instances
Actions in the task must be completed in a very specific order, and practicing the task to get better is easy	3	Value-add services (hiring, connecting) might involve some components for which reward functions can be defined
Total	**63**	

Table 5: Post-investment value-added Analysis

(f) *Exits:* On an average, VCs typically stay 4 to 6 years with their portfolio companies before divesting the company. As per the research study, 15% of exits is through IPOs, 53% are through M&A, and 32% are failures. Not all M&A activities are successful. These statistics vary for different types of VC firms. On an average, 9% of exits have a multiple greater than 10 and around 12% have multiple between 5 and 10. Not all IPOs result in high exit multiples. Early stage companies with an IPO exit have high multiples. There is wide range of outcomes for both IPO and M&A transactions across different types of VC firms. Deal selection is the most factor for high multiples especially for high IPO firms, followed by deal flow and post-investment value-add services. Deal flow is relatively more important for large investors, whereas value-add services is relatively more important for small investors. Additionally, there are other factors that matter more in success than in failure outcomes - luck, timing, VCs own contribution, and technology.

Item	Score	Comments
Input-Output information explicitly specified in machine-readable format	3	Control rights, exit scenarios, and potential outcomes are partially possible to specify
Information recorded or recordable by computer	3	Exit route, financing rounds, outcomes can be recorded by computer
Task does not require a wide range of complex outputs	1	Exit decisions require range of mental abilities (create exit strategy plan)
Task feedback is available through plentiful historical data	3	Feedback is received with different response times based on exit strategy
Output is error tolerant	1	Failure to exit a company might lead to negative returns
Not important that outputs are perceived to come from a human	1	Define control rights require negotiation between VC and Entrepreneur
Task does not require complex, abstract reasoning	1	Defining exit strategies and scenarios require complex reasoning
Task is mainly concerned with matching information to concepts, predictions, or actions	3	Different exit outcomes could be mapped to defined inputs (control rights, time, product market, and more).

Task does not require detailed, wide-ranging conversational interaction with a customer or another person	1	Exit decisions involve deep human conversations in order to define control rights and exit routes.
Task is highly routine and repeated frequently	1	Exit decisions are not a routine task
Task is describable with rules	3	Exit decisions might have some general rules to define exit strategies and exit route
No need to explain decisions during task execution	1	Exit decisions impact many stakeholders and require justification
Task can be converted to answering multiple choice questions, ranking options, predicting a number, or grouping similar objects	3	Exit decisions might be classified but identifying rules or criteria must be discovered
Long term planning is not required to successfully complete the task	1	Exit decisions involve planning a timeline of several years
Task might require working with text data	3	Exit decisions require reading market trend reports and exit strategy planning documents
Task might require working with image/video data	3	Exit decision may require utilizing images and videos to analyze trends, identify right timing
Task might require working with speech data	5	Exit decisions requires active communication between VC and entrepreneur
Task might require working with other types of digital data	1	Exit decisions does not involve utilizing other types of digital data
Many components of the task can be completed in a second or less	1	Exit decisions require long-term planning
Each instance of the task is similar to other instances in terms of executions; Actions can be measured	3	Exit decisions can be collected but outcomes are highly varied
Actions in the task must be completed in a very specific order, and practicing the task to get better is easy	1	Exit decisions involve negotiations that might be hard to practice
Total	**43**	

Table 6: Exits Analysis

(g) *Internal Organization of a VC firm:* As we have seen in Chapter 2, VC firms employs different kinds of professionals (average around 14 people with around 1.3 venture partners) - senior partners, managing directors, principals, associates, EIRs, back-end professional, and others. Early-stage VC firms are smaller with few junior deal-making professionals than late-stage firms. Late-stage VC firms work with companies that require more due diligence and also more number of people (especially associates). In about 60% of venture funds, partners specialize (especially small funds) in different tasks (fundraising, deal-making, deal sourcing, helping portfolio companies with networking activities). VCs work an average of 55 hours per week, with the largest amount of time working with the portfolio companies and then sourcing, selecting deals, and networking. These statistics vary across different types of VC firms and funds. VCs spend on average around 8 hours per week on managing their firms and about 3 hours per week managing LPs. In most cases, a specific partner is responsible for a particular portfolio company. About 74% of VC firms (especially medium-sized firms) compensate partners for individual success. Early-stage funds are more likely to compensate partners equally in order to support the need for cooperation. Roughly half of the venture funds require a unanimous vote of partners in initial investment decisions. Few funds require consensus while some require a majority vote.

Item	Score	Comments
Input-Output information explicitly specified in machine-readable format	1	Very difficult to identify individual skills and group decision-making capabilities that yield better performance outcomes
Information recorded or recordable by computer	1	Almost no input-output datasets exist
Task does not require a wide range of complex outputs	1	Requires a range of mental and physical abilities
Task feedback is available through plentiful historical data	1	Feedback takes very long time
Output is error tolerant	3	Mistakes could be fixed with some work
Not important that outputs are perceived to come from a human	1	Decisions are heavily based on human interactions
Task does not require complex, abstract reasoning	1	Decisions require complex reasoning
Task is mainly concerned with matching information to concepts, predictions, or actions	1	Very difficult to have clear, consistent inputs or outputs
Task does not require detailed, wide-ranging conversational interaction with a customer or another person	1	Requires deep interactions with humans
Task is highly routine and repeated frequently	3	Fairly routine decisions but could be done differently each time
Task is describable with rules	1	Specialized skill-based decisions or group decisions can't be easily described with rules
No need to explain decisions during task execution	1	Requires explanation during group-level decisions

Task can be converted to answering multiple choice questions, ranking options, predicting a number, or grouping similar objects	3	Some decisions may involve categorizing or identifying with patterns/rules that are easily discoverable
Long term planning is not required to successfully complete the task	1	Involves planning a timeline of several months
Task might require working with text data	5	Involves reading introductory emails, reading executive summary, business proposals, pitch deck
Task might require working with image/video data	3	Might involve creating marketing content, analyzing video introductions or pitches
Task might require working with speech data	5	Involves active communication, listening and talking activities
Task might require working with other types of digital data	3	Might involve analyzing market trends, company financials, and more.
Many components of the task can be completed in a second or less	3	Component decision tasks does not take long time to complete
Each instance of the task is similar to other instances in terms of executions; Actions can be measured	1	Difficult to summarize decisions with machine-readable data
Actions in the task must be completed in a very specific order, and practicing the task to get better is easy	1	Involves unique situations that hard to practice
Total	**41**	

Table 7: Internal organization of a VC firm Analysis

(h) *External organization of a VC firm:* Cash-on-cash multiples (average 3.5) and net IRR (average 24%) are most important benchmark metrics for most LPs. Performance of the fund relative to other VC funds and S&P 500 are also considered important by LPs. LPs are primarily motivated by absolute instead of relative performance for follow-on investing decisions and other performance incentives of VCs.

Item	Score	Comments
Input-Output information explicitly specified in machine-readable format	3	Possible to create some rankings/representation of incentives and their alignment, funds' performance data and follow-on investing decision outcomes
Information recorded or recordable by computer	3	Fund's performance data, market expectations, follow-on investing data can be recorded

Task does not require a wide range of complex outputs	1	Involves planning and strategizing to achieve required returns and follow-on investing
Task feedback is available through plentiful historical data	1	Accessing a fund's performance and related outcomes might takes 7-10 years
Output is error tolerant	1	Mistake could lead to damage of relationships between LPs and VCs
Not important that outputs are perceived to come from a human	1	Decisions require human connection
Task does not require complex, abstract reasoning	1	Decisions require complex reasoning
Task is mainly concerned with matching information to concepts, predictions, or actions	3	Possible to have clear inputs and outputs
Task does not require detailed, wide-ranging conversational interaction with a customer or another person	1	Requires interaction/negotiation between LPs and VCs
Task is highly routine and repeated frequently	1	Not routine decisions and involves different approaches every time
Task is describable with rules	3	Might be subject to some general rules related to follow-on investing, fund's performance
No need to explain decisions during task execution	1	Requires justification of decisions as most of them are long-term
Task can be converted to answering multiple choice questions, ranking options, predicting a number, or grouping similar objects	3	Some decisions may involve categorizing or identifying with patterns/rules that are easily discoverable
Long term planning is not required to successfully complete the task	1	Involves planning a timeline of several months
Task might require working with text data	5	Involves reading about market performance, writing investment proposals
Task might require working with image/video data	3	Might require working with images/videos align incentives, follow-on investing decisions
Task might require working with speech data	5	Involves active communication, listening and talking activities
Task might require working with other types of digital data	3	Might involve analyzing market returns, fund's performance financials, and more.
Many components of the task can be completed in a second or less	3	Component decision tasks does not take long time to complete
Each instance of the task is similar to other instances in terms of executions; Actions can be measured	1	Difficult to summarize decisions with machine-readable data

Actions in the task must be completed in a very specific order, and practicing the task to get better is easy	1	Involves unique situations that hard to practice
Total	**45**	

Table 8: External organization of a VC firm Analysis

Interviews and Case Studies

As part of research analysis, the author has analyzed few case studies of venture firms and AI companies in financial services industry who are experimenting or are using AI/data analytics tools and techniques in decision-making. Also, the thesis describes interview interactions (names of people can be disclosed because of privacy concerns) by the author of about 30 minutes with a couple of venture capital firms. In general, while interacting with academic scholars and professors, the author found out that people are very excited about the use and adoption of AI (quantitative approach) in venture capital industry. As more and more companies greatly shifting towards data-driven decision-making powered by rich data sources, relevance and adoption of AI, especially ML, is growing at a rapid pace in conventional industries. Venture firms (especially new-age firms) are actively using data-driven approaches (tracking the performance of portfolio companies using App Annie platform) to decision-making and also experimenting with AI techniques in order to build a competitive edge. A general trend that the author felt during his interactions with VCs was that young VCs were more receptive to the idea of AI being used for venture capital decision-making as compared to old and experienced VCs who showed some resistance and less enthusiastic (citing that there is not enough data available to build AI/ML models) about the adoption of AI in venture capital industry globally but who were convinced about using more data-driven approaches to venture capital.

(a) *Hone Capital*: Hone Capital is the US venture capital arm of CSC group, private equity firm in China. Founded in 2015, the US firm has invested over $100M in early to growth stage startups. The firm uses proprietary data-driven intelligence platform and a network of syndicate partners, and other VC firms to source and select deals [43]. The author interviewed with one of Associates in the firm who has worked on the intelligence platform. Here are few insights from the interview interaction as well as from news articles [44]:

- Their platform has performed at par with human-level judgments. In some scenarios, it has exceeded human-level performance.
- The platform is mainly used to source global early-stage high-quality deals.

- They have partnered with AngelList and are using AngelList APIs to connect to potential syndicate partners/leads and access the VC community. Also, they are using information about diverse early-stage deals for deal sourcing (doubled their deal flow - 10 to 20 deals per week).
- They have created their ML models (based on supervised learning function and network models) from database records of more than 30,000 deals from the last decade fetched from different sources, such as Crunchbase, PitchBook, and Mattermark. They explored around 400 characteristics per deal and have identified 20 characteristics for seed deals that are highly predictive of future success.
- The ML model filters and suggest companies based on total money raised, other investors' past conversion rate, founding teams' background (diverse universities), and syndicate partners' lead area of expertise. For some deals, the model suggested that company would be 70-80 percent successful, whereas on paper and analyzing the business model didn't convince human judgment otherwise.
- They don't rely on the ML model completely, but trust the model recommendations and usually use a combination of ML suggestions along with human judgments.
- They are convinced about the applicability of AI in other areas - portfolio optimization, deal selection, advanced levels of data extraction and analysis (analyzing pitch deck, social data, rich website data using google lighthouse) – in order to reduce various risks, increase ROI, and improve operational efficiency.

(b) *Data Collective*: Data Collective is a venture capital firm investing in entrepreneurs who are applying deep tech to disrupt giant industries. The firm has a unique operating model comprising of experienced venture capitalists and around 50 technology experts (CTOs, CIOs, Scientists, Engineers from top universities) and focusses on seed, series-A, and growth-stage companies (larger growth-stage fund size compared to seed-stage fund size) [45]. The author interviewed with one of the Principals in the firm and following are the insights from the interview:

- AI can't replace human decisions because of legal constraints, but definitely can be used to inform decisions.
- AI techniques could be utilized in deal sourcing, network and relationship management, deal selection, and exits decision-making scenarios.
- Valuations are based on heuristics and could be automated using advanced technologies.
- Deal sourcing involves professional network biases. AI could potentially improve deal sourcing and filtering by analyzed diversified deals.

- There are third-party platforms, such as Aingel.ai, that help in deal flow analysis, and deal sourcing, and investor-bias detection decisions.

(c) *Correlation Ventures*: Correlation Ventures is a new-age VC firm that aggressively uses data analytics in investment decisions. The firm is currently managing $350 million venture fund [46]. The firm's prime focus area is to become an ideal co-investor. The team claims to make investment decisions within two weeks or less. Correlation Ventures has invested huge resources in building in-house databases of venture capital financings (the US venture investments over the last 20 years) and record financing details, board members and management, investors, industry segments, stage of the business, and exit outcomes [46]. They use sophisticated proprietary predictive analytics model (not machine learning models) to improve US venture co-investments decision-making. The firm uses this selection model for all the investments they make. They also extract the data from all the readily-available documents provided by the startup company. With the extracted data and their vast historical knowledge base, the firm objectively evaluates potential co-investment opportunity rapidly. The selected firms and then finally reviewed by the investment committee before making an investment. This selection process not only yields better returns not only for the investors in the firm but also other co-investors involved in an investment deal. The author interviewed with one of the trusted advisors of this firm who also is a partner in another VC firm. Following are the insights from the interview:

- There is a challenge to build sophisticated ML models for decision-making in venture capital as there is not enough data available with mapped input variables and associated outcomes. It would take years to collect rich data to build such sophisticated models.
- It is also difficult to gather correct and unbiased information from the startup companies regarding co-investment deal opportunities, performance metrics, and more.
- Venture capital business is heavily based on professional networks and relationships. It is hard to build an AI system that could completely automate human decision-making in venture capital.

(d) *SignalFire*: SignalFire is an early-stage venture capital firm founded in 2013. They have built the firm around the principles to serve the entrepreneur across three main areas- recruit talent, expert advice, and corporate network access. The firm is managing $375 million seed as well as breakout fund to invest in seed companies [47]. The firm has three dedicated teams in-house: engineering, investment, and portfolio ops. The firm help entrepreneurs to grow their companies by designing and building products and services in-house. The firm has built a strong network of key experts in product development, marketing, sales, business development, and other areas to provide expert advice to the portfolio companies [48]. The firm has 50 advisors on the team that helps in sourcing high-quality deals [47]. The firm has built a sophisticated real-time ML platform (called Beacon) after spending many years of research and investing millions of dollars. The platform helps portfolio companies recruit talent by tracking and raking world's top engineers from around 10 million sources (web pages, social platforms, and more) [47]. The firm also tracks and monitors around 6 million companies in real-time to understand consumer behavior and spend, app usage, and other market and competition related metrics.

(e) *Google Ventures*: Founded in 2009, Google Ventures is the venture capital business of Alphabet with under $1.5 billion under management and is investing in cutting-edge technologies in the areas of healthcare, robotics, transportation, cyber-security, agriculture, and more [49]. The firm has talented engineers, scientists, physicians, investors, and marketers who along with Google's unique talent and resources provide support to the portfolio companies. The venture firm heavily relies on data (access to world's largest data-sets) and cloud computing infrastructure to gather and clean data from the academic literature, due diligence about startup companies and founders, past experience, and other sources to feed into algorithms that help identify what factors are important in analyzing different kinds of deals [49]. The firm still relies on intuition and chemistry that can sometimes override the data. In one of the interviews with NY times [49], former CEO of Google Ventures said that - "We would never make an investment in a founder we thought was a jerk, even if all the data said that this is the investment you should make. We would make an investment in a founder we really believed in, even if all the data said we're making a mistake. But it would give us pause."

Apart from these firms, there are many other VC firms across the globe who are using quantitative approach (using AI/ML models and data analytics in varying capacities) to venture capital – Greylock Partner, AI VC, FloodGate, Kleiner Perkins Caufield & Byers (they have built proprietary data-mining software called Dragnet), DFJ Ventures, Index Ventures, Nauta Capital (they have built predictive models to access success or failure of a startup company), Fly Ventures, EQT Ventures (following hybrid startup and VC firm approach to source deals using their proprietary platform called Motherbrian [50]). AI startups, such as Kensho Technologies, Alpha Sense, Decissio, are also helping VC firms leverage AI to sort out important information from vast data-sets and aid investment decisions.

Chapter 5: Results of Research Findings

As we have seen in the feasibility analysis (Chapter 4) of decision-making in eight value chain areas of a venture capital firm, deal selection scored the maximum while deal structure scored the minimum. Below diagram shows the AI automation feasibility range for decision-making in the eight areas:

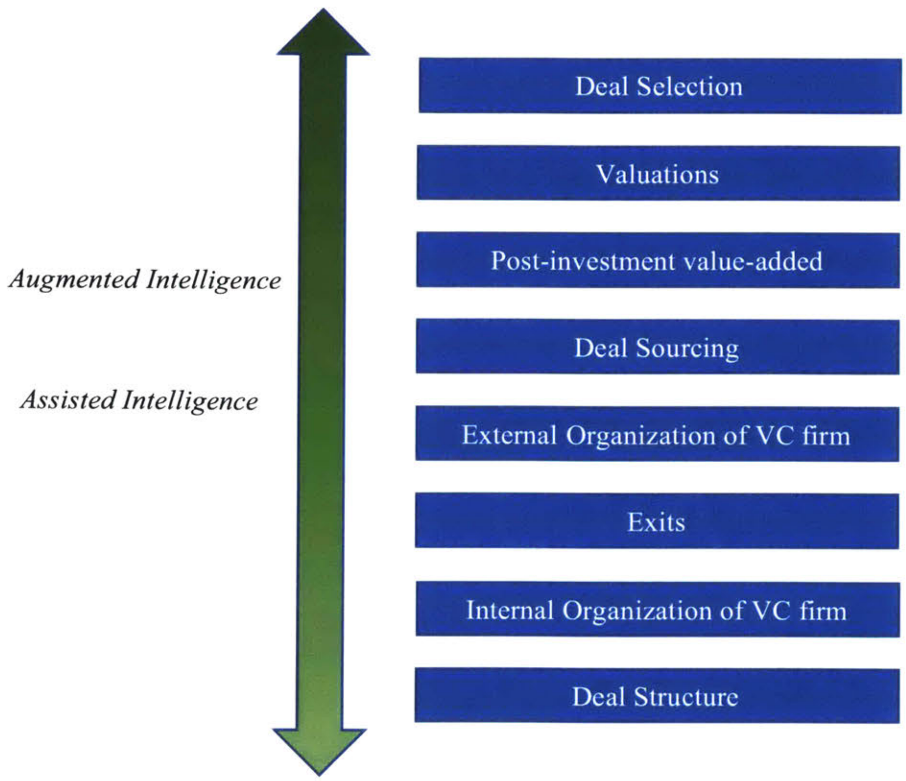

Figure 22: Relative AI automation feasibility of decision-making in venture investing

As we seen in the above figure, the AI automation feasibility of decision-making in different value chain areas has been ranked relative to one other (based on the relative scores out of 105 in feasibility analysis in Chapter 4). Decisions with scores above 70 upwards till 95 are considered to augment human intelligence in an increasing order from 70 to 95, whereas decisions with scores below 60 downwards are considered to assist human intelligence in a decreasing order from 60 to 21. These bounds are calculated based on author's knowledge of the AI field and of reference scores of other tasks and decisions in other professions. Decision-making in deal selection area can most augment human intelligence, whereas decision-making in deal structure area can least assist human intelligence.

Use-cases for AI automation

Some of the possible use-cases that could be automated using AI tools and techniques in the decision-making of the eight value chain areas of a venture capital firm:

(a) *Building psychological profile of an entrepreneur/employees*: NLP and Text analytics, along with machine learning models, could be used to build a psychological profile of an entrepreneur. There are several attributes (see figure below) of an entrepreneur that defines his or her psychology. As per research study done by Barclays [51], there are broadly two different types of entrepreneurs: Type A who are artistic, well-organized, highly competitive, emotionally stable, neither extrovert nor introvert, and Type B who are traditional, spontaneous, team-player, emotional, neither extrovert nor introvert. These attributes could be analyzed by scraping textual data and parsing images/videos from social profiles (Facebook, Twitter, LinkedIn) which then could be modeled to build the psychological profile of an entrepreneur and accordingly access (using supervised learning functions) the entrepreneur-fit in different scenarios. Psychological profile could be used to support decision-making in deal sourcing, deal selection, deal structure, post-investment value-added, and exits scenarios.

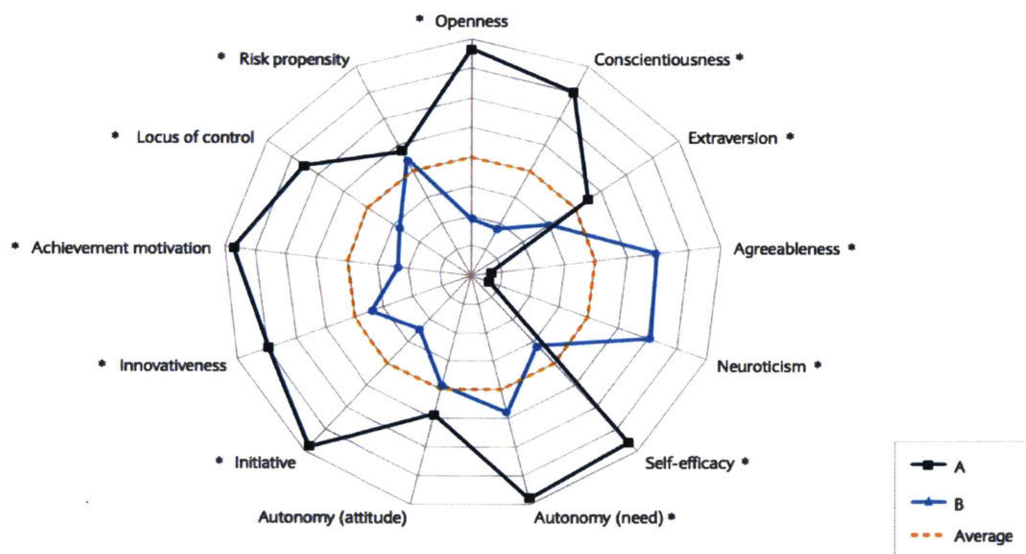

Figure 23: Psychological Attributes of an Entrepreneur [51]

Apart from accessing the psychological attributes of an entrepreneur, VCs could also access the relative psychological attributes (see figure below) of other members of the team/company in a similar fashion.

These relative profiles could be used by VCs to support decision-making in the deal selection, deal structure, and post-investment value-added scenarios.

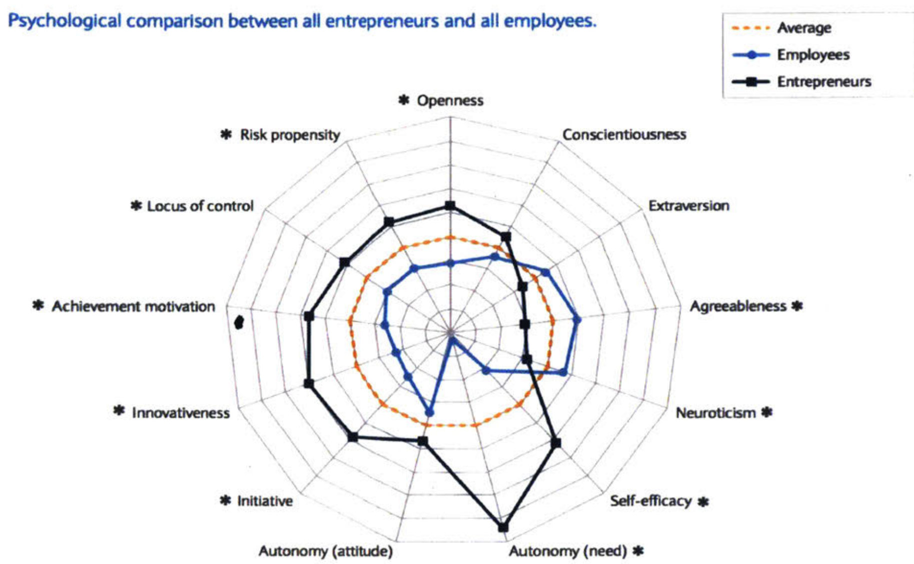

Figure 24: Relative Psychological attributes of employees and entrepreneur [51]

(b) *Professional Network Management*: Many VC firms are using CRM tools to manage their deal flow process. As we have seen in the analysis chapter that professional networks and referrals form the basis of many investment decisions. Machine learning and text analytics could be used to develop smart intelligent agents that maintain and strengthen VC's professional network and help connect with the right professional depending on need contexts (referrals/strategic advisors, introductions, connecting customers, connecting investors). Email engagement, social profiles, online startup platforms, contacts directory, and other data sources could be used to extract data and build intelligent tools (using bipartite networks and graph theory to map distinct entities and their relationships) that could assist VCs in effectively managing and using their professional networks.

(c) *Assessing Team Dynamics*: As we have seen in the feasibility analysis that entrepreneurial team (especially top management) is one of the most important factors for the success of any startup company. Group level attributes, such as commitment, clarity of role, shared leadership (inspire others for the common goal), constructive conflict, negotiation, psychological safety (idea generation and feedback loop), are some of the key determinants of team dynamics in startup companies [52]. Traditionally, it has been difficult for VCs to access group level team dynamics. However, guided team interactions can be recorded and captured in several video formats that could be then analyzed using advanced vision (video content analysis technologies) and NLP technologies to identify and map group level attributes in order to access the overall quality of team dynamics.

(d) *Selecting Syndicate partners*: As we have seen in the feasibility analysis, selecting syndicate partners is crucial in a deal selection, deal structure and post-investment value-added scenarios in order to effectively manage investment risks. Selecting partner syndicates, as well as the lead syndicate, are critical decisions in these scenarios. Though professional networks play a huge role in selecting right syndicates, VC firms have a large pool of syndicate partners (online as well as the physical world) to select from. In 2015, a $163M amount was invested in seed stage companies through online syndicates, 53% more than in 2014 [53]. Traditionally, VCs have been selecting partners from a small group of preferred partners (usually from within preferred-partner circles having similar functional styles, industry knowledge, local markets knowledge). Machine learning models (built using unsupervised learning functions), web scraping, and text analytics could be used to build a smart tool that extracts and analyzes data from professional networks and online syndicate platforms (such as AngelList) to identify right mix of partners as well as lead investor (based on fund size and performance) for a particular investment-round.

(e) *Recruiting employees or top management*: Recruiting employees and top management is one of the key value-added services that VCs provide post-investment. Machine learning models (using supervised as well as reinforcement learning functions), along with NLP, could be used to extract data from multiple online sources, such as LinkedIn, AngelList, Crunchbase, Research Gate, GitHub, competitors team sites, Patents database, and others, to construct fitment profile of potential recruits. These profiles (quantified based on passion/drive, cultural fit, go-getters, flexible, humility attributes deduced from keywords, frequency of job change, career growth, responsibilities, recommendations) could then be assessed for overall company fitment by pattern matching with profiles of past or ideal employees for success and failure outcomes (accessed via rewards, news articles, growth in the company) in similar job roles.

(f) *Portfolio construction*: Artificial Neural Network (ANN) algorithms could be used to determine diversified deal allocation in a venture fund. ANN models have shown higher performance than traditional financial models in different markets, such as real estate, mortgage, stock, and accounting [54]. ANN models have several layers - input layer (a unit which receives input that network will learn), output layer (a unit that responds with learned information about the input), and hidden layer (multiple layers between input and output that transforms input into a usable element that could be used by output). ANN models could capture the non-linear property in the algorithmic model and overcome VC's unstructured decision-making process and market uncertainty. ANN models could be further optimized to consider the analysis of portfolio company's strength/weakness, sector, stage, value-add, geography, funds' investment thesis, and market dynamics and to spot the optimal point on the efficient frontier.

(g) *Deal flow and deal sourcing*: We have seen in case study analysis that many VC firms are using ML models to source high-quality and diversified set of deals from numerous sources containing structured, semi-structured, and unstructured data. Deep learning ML models could be also used to source deals (even those startup companies that are working under the radar) by analyzing various signals - social signals, referral signals, growth and funding signals. Social signals include tracking and analyzing data from blogs, news articles, academic research, patents, accelerators, online databases - Crunchbase, YourStory, Startup Stash, CBInsights, and successful entrepreneur's background and social profile (tracking profile changes to access whether the entrepreneur is likely to start a new company or not). Referral signals include identifying the key sources of a network (online or social network relationships, enterprise/company network relationships, portfolio companies network relationships) and also the strength of referral or source of a deal. Growth and funding signals include tracking and analyzing latest funding deal information from the news article or social platforms, company cash flows, product usage, job boards, company websites, and customer reviews. Additionally, ML models (unsupervised learning functions) could be used to classify and bucket deals into different categories.

(h) *Identifying New Markets*: ML models (Deep Neural Nets) along with NLP could also be used to track and analyze consumer behavior buying and spending patterns, new technology trends, customer fragmentation per market, analyst reports, competitive relationships, market timings in order to discover new patterns that signal early market creation. This would help VCs in constructing venture fund investment thesis.

(i) *Deal selection*: Expert systems could be utilized in deal selection decisions. As we have seen in Chapter 4, most final deal selection decisions involve group decision-making scenarios. AI enable expert system could be used as an additional decision-maker that would output a final vote for a particular deal selection. Expert system could consider either same or different deal selection parameters (strength and background of entrepreneur, management team, deal summary, pitch deck, due diligence information, and others) in order to decide whether to invest in a company or not. Also, ML models (supervised learning functions) along with integer programming could be used to predict whether a company who would be successful or not [1].

(j) *Reserve Planner for portfolio companies*: ML models (supervised and reinforcement learning functions) could be used directly to predict the reserves allocation for portfolio companies. The system could analyze past reserves data for portfolio companies that mimic reservation rules followed by VC firm and could input financial simulations data to predict reserves required for portfolio companies in future. VCs could use such models to optimize capital calls from LPs and accordingly plan follow-on financing rounds.

Artificial intelligence adoption framework

As we have seen in Chapter 3, AI adoption is faster in more digitalized sectors. Companies are utilizing AI to improve the core of their businesses. Traditionally, venture capital industry is largely driven by human relationships and interactions. The industry utilizes few digital assets but is quite behind using intelligent IT systems to improve business operations or decision-making. Based on the above analysis and research, venture capital firms should utilize suggested framework (see figure below) to adopt AI tools and techniques to improve venture capital decision-making.

The adoption framework model suggests to streamline, capture and integrate data from possible sources in order to generate rich and diversified data-sets that could be utilized for AI automation. This could be done by capturing data (potentially by using easy-to-use cloud infrastructure) related to various decision-making scenarios and potential outcomes of those decisions. Also, firms could partner with third-party software companies to help gather and streamline various data sources.

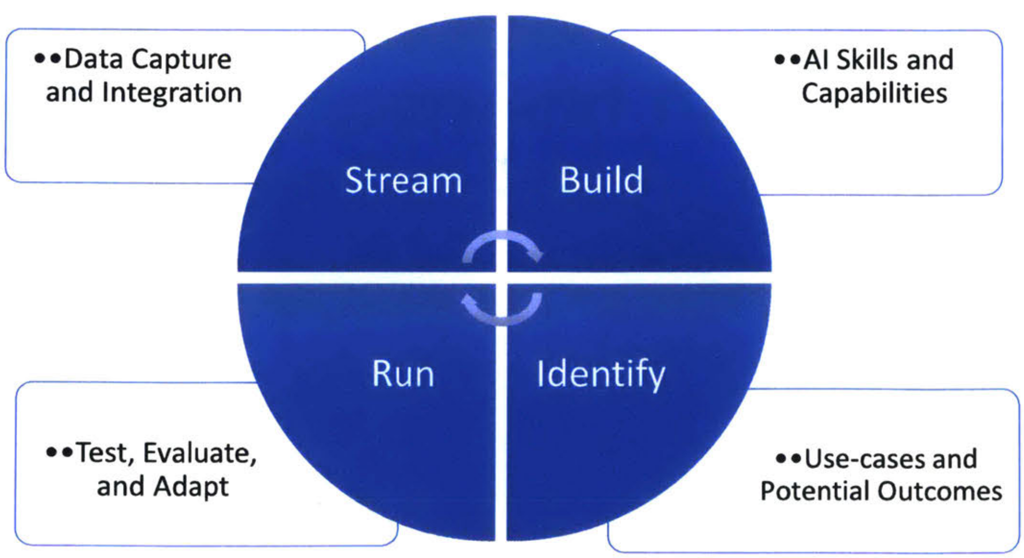

Figure 25: AI Adoption Framework in Venture Capital

Further, the model suggests building strong AI skills and capabilities in-house by hiring talented data science and engineering teams who can easily grasp and understand the operation model of venture investing. Venture partners should then discover and identify potential decision-making use-cases along with potential outcomes that could be addressed by AI tools and techniques. Lastly, the firm should build or leverage required AI tools or techniques to address the desired use-cases. The AI systems hence developed should be thoroughly tested and evaluated again various decision outcomes. The AI systems should be carefully adapted to existing workflows and should be continuously improved over time. VC firms need to remain flexible and monitor the progress throughout the adoption cycle in order to successfully benefit from AI systems.

Impact of Artificial intelligence technology adoption

Economics benefits to a Venture Capital firm

AI adoption in decision-making scenarios can greatly benefit VC firms. For a VC firm, the use of AI tools and techniques will improve fund's returns, help reduce various risks related to fund's portfolio management, portfolio companies, and relationships with LPs, improve operational efficiency, increase VCs' performance incentives, clear fund strategy, reduce average fund's lifecycle, and reduce network biases, similarity biases, and gender biases.

Impact on startup ecosystem and fundraising

As more and more VC firms start adopting AI for investment decisions, the significance of online startup related platforms (such as AngelList, Crunchbase, Gust, Yourstory, and others) would increase, resulting in stronger network effects and more user engagement. More and more entrepreneurs would start using such centralized platforms and provide more accurate information about themselves and their company internals. VCs would also start using such platforms to profile their venture funds and connect with diversified sets of companies and founders. At the same time, online platforms would evolve and create sophisticated product workflows in order to ensure the accuracy of the information provided by different users. This would result in easy access to information related to all the players involved in the fundraising process. More and more startups would get an opportunity to reach out to multiple investors and to be considered for fundraising activity. At the same, it might result in perfect competitive market in which all the players in the ecosystem have the same access to all the information. These engagements might result in more companies being funded in shorter cycles, increasing the probability of companies becoming unicorns or exiting successfully in the market. On the other hand, there could be possibilities that deserving founders and bright companies who fail to highlight their capabilities might not get detected by AI systems and in turn not get funded by an investor.

Challenges and risks in technology adoption

Build expert systems that would support decision-making in venture investments is still a long way to go. As we have seen in Chapter 5 that AI would be best suitable to act as an augmented intelligent agent that supplements human decision-making in venture capital. However, there are many challenges involved in AI adoption - lack of rich data-sets and data ecosystem, resistance from old and experienced VCs to adapt AI in venture capital, building AI skills and capabilities in-house, less accurate experimental verified results of AI adoption in investment decision-making, legal boundaries, over-reliance on professional networks for decision-making, and unclear potential business use-cases and associated outcomes. Nonetheless, these challenges are being addressed and AI adoption could become easy and smooth in coming future. Successful AI adoption also possess some major risks [55] - misaligned VCs objectives, achieve superhuman capabilities (evolution after expert systems or sophisticated deep neural net algorithms), unanticipated negative consequences that could result in huge financial and economic loss, fast growth in machine capabilities that makes it harder to experiment different scenarios, learn and adapt human biases in computation.

Chapter 6: Conclusion and next steps

Summary

Artificial Intelligence technologies are widely being adopted in the decision-making scenarios across a company's value chain in many different industries. Specifically, AI adoption in financial services is growing at a rapid pace to improve decision-making in customer-focused, operations-based, trading-based, and regulatory-based use-cases. Venture firms (especially new-age firms) are actively using data-driven approaches (tracking the performance of portfolio companies using App Annie platform) to decision-making and also experimenting with AI techniques in order to build a competitive edge. Young VCs are more receptive to the idea of AI being used for venture capital decision-making as compared to old and experienced VCs who have some resistance and are less enthusiastic (citing that there is not enough data available to build AI/ML models) about the adoption of AI in venture capital industry globally but who are convinced about using more data-driven approaches to venture capital. The feasibility analysis of decision-making process in eight value chain areas of a venture capital firm - deal sourcing, deal selection, valuations, deal structure, post-investment value-add, exits, internal organization of VC firm, external organization of VC firm - showed that AI could best augment human intelligence and not completely replace human decision-making. Decision-making in deal selection area can most augment human intelligence, whereas decision-making in deal structure area can least assist human intelligence. There are several possible decision-making use-cases that could be automated using AI tools and techniques in venture capital - Building psychological profile of an entrepreneur/employees, Professional Network Management, Assessing Team Dynamics, Selecting Syndicate partners, Recruiting employees or top management, Portfolio construction, Deal flow and deal sourcing, Identifying New Markets, Deal selection, Reserve Planner for portfolio companies, and more. Successful AI adoption framework in venture capital should build data ecosystems, build AI skills and capabilities in-house, identify decision-making use-cases and associated outcomes, and finally experiment, evaluate and adapt AI systems in the organizations. Though there are several opportunities and associated risks involved in using AI for decision-making in venture capital, the future looks bright and more and more VC firms would use AI tools and techniques to support human decision-making in venture investment.

Limitations

The purpose of the thesis was to evaluate the extent of using AI tools and techniques in decision-making scenarios in venture capital and identify some use-cases along with associated risks involved in AI adoption.

The author has analyzed the feasibility only across eight value chain areas of a venture capital firm - deal sourcing, deal selection, valuations, deal structure, post-investment value-add, exits, internal organization of VC firm, external organization of VC firm – based on is knowledge and using quantitative data points from a reference survey results of how decisions are made by VCs in 681 venture firms (not representative of global decision-making process in venture firms across all value chain areas).

Next Steps

Continued research should be done to first improve the accuracy of feasibility analysis scoring of decision-making across eight value chain areas by reviewing or surveying these by a large number of VC firms. Subsequently, more concrete sub decision-making use-cases, input variables, and associated outcomes should be identified. Required data-sets should be collected from rich and diversified sources to get more accurate outcomes. These use-cases should be simulated and tested for accuracy by comparing results from human decision-making alone in similar scenarios. The results should be shown to different types of VCs to get practical feedback whether these models could replace, supplement, or support human decision-making and also on their future adoption criteria.

REFERENCES

[1] D. S. Hunter and T. Zaman, "Picking Winners: A Framework For Venture Capital Investment," *ArXiv170604229 Q-Fin Stat*, Jun. 2017.

[2] "Inside The Global Q1 2017 VC Market," *Crunchbase News*. [Online]. Available: https://news.crunchbase.com/news/inside-global-q1-2017-vc-market/. [Accessed: 28-Jan-2018].

[3] "Artificial intelligence: the investment of 2017 and beyond," *Financier Worldwide*. [Online]. Available: https://www.financierworldwide.com/artificial-intelligence-the-investment-of-2017-and-beyond/. [Accessed: 26-Jan-2018].

[4] Kaplan, Steven N. and Lerner, Josh, "It Ain't Broke: The Past, Present, and Future of Venture Capital. Journal of Applied Corporate Finance," vol. Vol. 22, No. 2, p. 36–47, Spring 2010.

[5] "Venture capital," *Wikipedia*. 25-Jan-2018.

[6] Andrew Woods, "An Investor's Guide to Venture Capital," *Crowdmatrix*, 29-May-2017. .

[7] M. Charafeddine, "The VC Value Chain (Part 1)," *ArzanVC Insights*, 24-May-2016. .

[8] J. Mendelson and B. Feld, *Venture Deals, 3rd Edition [Book]*. .

[9] J. Skyler Fernandes, "The Venture Capital Process," 11:45:21 UTC.

[10] P. Gompers, W. Gornall, S. Kaplan, and I. Strebulaev, "How Do Venture Capitalists Make Decisions? by Paul A. Gompers, Will Gornall, Steven N. Kaplan, Ilya A. Strebulaev :: SSRN," *Stanf. Univ. Grad. Sch. Bus. Res. Pap. No 16-33 Eur. Corp. Gov. Inst. ECGI - Finance Work. Pap. No 4772016*, Aug. 2016.

[11] A. Romans, *The Entrepreneurial Bible to Venture Capital*. 2013.

[12] Contributor, "Strategies For VCs To Increase Startup Success Odds," *TechCrunch*. .

[13] "Private Capital Markets - Legal Templates & Insights - VC Experts." [Online]. Available: https://www.vcexperts.com/buzz_articles/297. [Accessed: 28-Jan-2018].

[14] 8VC, "Do VCs Know What Entrepreneurs Really Want?," *8VC News*, 06-Jun-2017. .

[15] "Fundraising Stages for Startup – CArocked." [Online]. Available: https://carocked.wordpress.com/2016/06/26/fundraising-stages-for-startup/. [Accessed: 28-Jan-2018].

[16] "Paul Gompers et al - Specialization and Success: Evidence from Venture Capital. Available - http://www.people.hbs.edu/jlerner/VCSpecialize.September%2029%202008.pdf." .

[17] Damien Steel, "Raising Venture Capital," 13:59:25 UTC.

[18] K. Bailey, "Reframing the 'AI Effect,'" *Katherine Bailey*, 27-Oct-2016. .

[19] "Artificial intelligence," *Wikipedia*. 27-Jan-2018.

[20] "Artificial Intelligence and its Use Cases in Publishing | Home." [Online]. Available: https://www.rave-tech.com/artificial-intelligence-and-its-use-cases-in-publishing/. [Accessed: 28-Jan-2018].

[21] "China Upgrades Logistics as Alibaba Goes Amazon," *Asian Robotics Review*. [Online]. Available: http://asianroboticsreview.com/home75.html. [Accessed: 28-Jan-2018].

[22] "MGI - Artificial Intelligence The Next Digital Frontier? Available - https://www.mckinsey.com/~/media/McKinsey/Industries/Advanced%20Electronics/Our%20Insights/How%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/MGI-Artificial-Intelligence-Discussion-paper.ashx." .

[23] E. Brynjolfsson and T. Mitchell, "What can machine learning do? Workforce implications," *Science*, vol. 358, no. 6370, p. 1530, Dec. 2017.

[24] "Artificial Intelligence," *Put AI in Its Place*. [Online]. Available: http://www.topsigma.com/. [Accessed: 28-Jan-2018].

[25] J. Bughin, B. McCarthy, and M. Chui, "A Survey of 3,000 Executives Reveals How Businesses Succeed with AI," *Harvard Business Review*, 28-Aug-2017. [Online]. Available: https://hbr.org/2017/08/a-survey-of-3000-executives-reveals-how-businesses-succeed-with-ai. [Accessed: 28-Jan-2018].

[26] "M.-C. Chan et al- Artificial Intelligence in Portfolio Management. Available - https://link.springer.com/content/pdf/10.1007%2F3-540-45675-9_60.pdf." .

[27] M. T. R. Insights, "AI Drives Better Business Decisions," *MIT Technology Review*. [Online]. Available: https://www.technologyreview.com/s/601732/ai-drives-better-business-decisions/. [Accessed: 28-Jan-2018].

[28] "Why AI Drives Better Business Decision-Making," *Salesforce Blog*. [Online]. Available: https://www.salesforce.com/blog/2017/11/why-ai-drives-better-business-decision-making.html. [Accessed: 28-Jan-2018].

[29] I. Lunden, "Prowler.io nabs $13M for its new approach to decision making in AI," *TechCrunch.* .

[30] L. Xia, "Improving Group Decision-Making by Artificial Intelligence," in *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence (IJCAI-17).*

[31] "The Financial Stability Board - Artifical Intelligence and Machine Learning in Financial Services. Available - http://www.fsb.org/wp-content/uploads/P011117.pdf." .

[32] "Artificial intelligence and machine learning in financial services - Financial Stability Board." [Online]. Available: http://www.fsb.org/2017/11/artificial-intelligence-and-machine-learning-in-financial-service/. [Accessed: 28-Jan-2018].

[33] PricewaterhouseCoopers, "Artificial intelligence and digital labor in financial services," *PwC.* [Online]. Available: https://www.pwc.com/us/en/industries/financial-services/research-institute/top-issues/artificial-intelligence.html. [Accessed: 28-Jan-2018].

[34] S. R. Reeves David Kiron, Philipp Gerbert, and Martin, "Reshaping Business With Artificial Intelligence," *MIT Sloan Management Review.* .

[35] J. Greathouse, "Two Trends That Are Transforming Venture Capital," *Forbes.* [Online]. Available: https://www.forbes.com/sites/johngreathouse/2016/11/12/two-trends-that-are-transforming-venture-capital/. [Accessed: 28-Jan-2018].

[36] "5 Trends Transforming the World of Venture Capital." [Online]. Available: /wisdom/5-trends-transforming-the-world-of-venture-capital/. [Accessed: 28-Jan-2018].

[37] "Venture Capital 20/20: Trends to Expect in the Years Ahead." [Online]. Available: http://www.milkeninstitute.org/videos/view/venture-capital-2020-trends-to-expect-in-the-years-ahead. [Accessed: 28-Jan-2018].

[38] J. Klunzinger, "The OSF Playbook: A Journey to Investing in Future Sci-Tech," *OS Fund.* .

[39] B. Anant, "Evaluating the Risk — Reward Relationship Across Funding Rounds," *Medium*, 29-Feb-2016. .

[40] S. Nasser, "Valuation For Startups — 9 Methods Explained," *Startups & Venture Capital*, 14-Jun-2016. [Online]. Available: https://startupsventurecapital.com/valuation-for-startups-9-methods-explained-53771c86590e. [Accessed: 28-Jan-2018].

[41] "Chan - 2007 - How Do Venture Capital Investors Add Value to Portfolio companies? Avaiable -

https://www.pillsburylaw.com/images/content/2/4/v2/2430/3FE607E19A8B7AAC87B931FDD8614997.pdf"

[42] "Venture Capital Exits," *ResearchGate*. [Online]. Available: https://www.researchgate.net/publication/228299051_Venture_Capital_Exits. [Accessed: 28-Jan-2018].

[43] "Home | Hone Capital." [Online]. Available: http://honecap.com/. [Accessed: 28-Jan-2018].

[44] "A machine-learning approach to venture capital | McKinsey & Company." [Online]. Available: https://www.mckinsey.com/industries/high-tech/our-insights/a-machine-learning-approach-to-venture-capital. [Accessed: 28-Jan-2018].

[45] "Data Collective - DCVC." [Online]. Available: https://www.dcvc.com/. [Accessed: 28-Jan-2018].

[46] "Correlation Ventures." [Online]. Available: http://correlationvc.com/. [Accessed: 28-Jan-2018].

[47] "SignalFire Raises $330 Million for Data-Centric Venture Capital - WSJ." [Online]. Available: https://www.wsj.com/articles/signalfire-raises-330-million-for-data-centric-venture-capital-1494415804. [Accessed: 28-Jan-2018].

[48] C. Farmer, "Announcing SignalFire," *SignalFire*, 14-Oct-2015. .

[49] C. C. Miller, "Google Ventures Stresses Science of Deal, Not Art of the Deal," *The New York Times*, 23-Jun-2013.

[50] "Here's How EQT Ventures' Motherbrain Project Will Find The Next Unicorn - Swedish Startup Space." [Online]. Available: http://swedishstartupspace.com/2016/03/29/heres-how-eqt-ventures-motherbrain-project-will-find-the-next-unicorn/. [Accessed: 28-Jan-2018].

[51] "Greg Davis - The psychology of entrepreneurship. Available - https://www.home.barclays/content/dam/barclayspublic/images/news-newsite/2015/06/Barclays%20report%2020150616v1-final.pdf." .

[52] "Valtter Vihervuori - Accesing Startup Team and Team Dynamics from an Investor's perspective. Available - https://aaltodoc.aalto.fi/bitstream/handle/123456789/29278/master_Vihervuori_Valtter_2017.pdf?sequence=1." .

[53] L. Coppey, "VC Firms and AngelList Syndicates: Friends or Foes?," *Medium*, 01-Sep-2016. .

[54] "Artificial Intelligence in Portfolio Management," *ResearchGate*. [Online]. Available: https://www.researchgate.net/publication/221252939_Artificial_Intelligence_in_Portfolio_Management. [Accessed: 28-Jan-2018].

[55] "Potential Risks from Advanced Artificial Intelligence," *Open Philanthropy Project*, 26-Aug-2015. [Online]. Available: https://www.openphilanthropy.org/research/cause-reports/ai-risk. [Accessed: 28-Jan-2018].

APPENDIX

Rubric [23]

1. Information needed to complete the task (inputs) and outputs can be explicitly specified in machine-readable format

1: It is very difficult or impossible to identify particular inputs and outputs (e.g. emotions, ideas, impressions)

3: It is possible to create rankings or partial representability of inputs and outputs

5: It is easy to quantify results on a machine/computer (e.g. calculations, concrete inputs and outputs)

2. Task information is recorded or recordable by computer

1: Input and training outputs in separate, incompatible databases, or not online at all (e.g. no dataset exists at all)

3: Some inputs and training outputs online/can be observed by computer (e.g. sensors can be installed at low cost to generate necessary data - includes places where images, video, or sound data can be recorded but may not be yet).

5: Inputs and training outputs already online in consistent format (e.g. queries can be made to a database to get necessary information)

3. Task does not require a wide range of complex outputs (mental and/or physical)

1: Task requires a range of different mental **or** physical abilities (e.g. performing a difficult surgery, completing an obstacle course, acting in a film, creating a plan, negotiating)

3: Tasks requires moderate variety in responding and acting (e.g. walking a dog, supervising a construction site, inspecting a building)

5: Task requires very little variety in thinking or action/movement (e.g. sorting mail, doing taxes, labeling an image)

4. Task feedback (on the success of outputs) is immediate or available through plentiful historical data.

1: Feedback is never received or takes a long very long time (e.g. predictions may take months or years until accuracy can be proven, it takes years often, to determine the success of writing a business plan)

3: Feedback is received but response time is inconsistent/unclear and/or unclear on if it is beneficial to progress (e.g. teaching quality can be measured through standardized tests and observations, which are neither immediate nor long-term)
5: Instant results/feedback when the action is executed (e.g. calculations can be immediately categorized as either correct or incorrect)

5. The task output is error tolerant
1: A mistake could lead to serious harm, injury, or death to those involved, or could lead to lasting negative consequences (e.g. mistake during surgery, mistake at a nuclear facility)
3: A mistake will have negative consequences, but can fixed with some work (e.g. a construction mistake, or human resources slip-up will be noticed and reprimanded, but would not result in termination of employment or injury)
5: A mistake can be easily fixed, and holds few, if any negative consequences (e.g. a slip up in factory work or mail sorting mistakes could go potentially unnoticed)

6. It is not important that outputs are perceived to come from a human
1: Task fundamentally requires human connection (e.g. therapy, teaching, making a speech, delivering bad news like a diagnosis)
3: Task could be done by a non-human, but might cause frustration or inefficiency (e.g. customer service)
5: Task requires little human connection, empathy, or emotional intelligence (e.g. telemarketing, preparing taxes, performing calculations, lifting boxes)

7. Task does not require complex, abstract reasoning
1: Task requires intuition or highly involved reasoning (e.g. writing a plan, administering therapy, coming up with a research proposal/plan, teaching)
3: Task requires some reasoning, but can mostly be broken into well-defined rules (e.g. playing chess, sorting mail)
5: Task is mainly perception and does not require complex reasoning skills (i.e. can be done in less than 1 second)

8. Task is principally concerned with matching information to concepts, labels, predictions, or actions
1: The task does not have clear, consistent inputs or outputs (e.g. open-ended travel vacation)

3: The task potentially has well-defined inputs and outputs, but does not require mapping of the two (e.g. middle management, camp counselor, kindergarten teacher)
5: The task has clear inputs and outputs. The purpose of the task is to determine how the inputs affect the outputs (e.g. translating one language to another, matching an image to words describing the image)

9. Task does not require detailed, wide-ranging conversational interaction with a customer or other person
1: Task requires explaining something deeply to another person, or having a deep conversation that cannot be predicted in advance (e.g. therapy, negotiation)
3: Task involves communicating but about a relatively small, pre-set range of topics (e.g. giving instructions or directions, answering/asking specific/common questions)
5: Task doesn't require any form of communication/conversation with another person (e.g. solving equations, lifting objects, observing)

10. Task is highly routine and repeated frequently
1: Task is not routine, and different approaches must be taken every time (e.g. negotiating contracts, fighting a fire, treating rare and specific issues)
3: Task is routine, but might be done differently each time (e.g. waiting tables, operating a multi-purpose machine, teaching a class)
5: Task is very repetitive, and must be done in the same way each time (e.g. working in an assembly line, delivering things along a route, being a cashier)

11. Task is describable with rules
1: The task has no clear, well-known set of rules on what is and is not effective (e.g. inventing a product, dealing with exceptions, painting a painting, writing a book)
3: The task may be subject to some general rules (e.g. cutting hair, making a chair, overseeing a construction site, driving a car)
5: The task can be fully described by a detailed set of rules (e.g. folding origami, following a recipe, determining loan eligibility via formula)

12. There is no need to explain decisions during task execution
1: Decisions highly impact the lives of others and require justification (e.g. persuasion, long term planning, law-making, courtroom decisions)

3: There is some need to explain decisions, particularly when people ask questions (e.g. doctors performing checkups, operating machinery)

5: There is no need to explain decisions. The task is only concerned with having the correct output, and does not depend on the process through which the output is determined. (e.g. correctly predicting the weather, performing the correct calculation, optimizing allocation of resources, determining quickest route)

13. Task can be converted to answering multiple choice questions, ranking alternative options, predicting a number, or grouping similar objects

1: Task output does not have to do with any of these options (e.g. lifting objects, collecting things, making things)

3: Task output may have something to do with categorizing or identifying things but the rules or criteria are not clear in advance and must be discovered (e.g. Supervising others, making sure that a team stays on track, recommending a plan)

5: Task is focused on applying a rule or pattern, particularly related to sorting or grouping things (e.g. grading food quality, recognizing faces, diagnosing common conditions, sorting mail)

14. Long term planning is not required to successfully complete the task

1: The task is concerned with planning around a timeline of months or years (e.g. supervising research projects, constructing complex buildings, entrepreneurship, crafting long term cancer treatment plans)

3: The task is concerned with a timeline in the range of weeks or days or an indeterminate amount of time (e.g. managing others' workloads, teaching students a specific set of lessons)

5: The task involves an immediate response and isn't concerned with a future impact (e.g. answer questions in a call center, lifting objects, performing calculations)

15. The task requires working with text data or might require working with text in the future:

1: Task does not include working with any text (e.g. making a hamburger, operating machinery)

3: Task may include some light reading (e.g. reading labels, occasionally reading directions)

5: Task includes heavy text processing, reading, or writing (e.g. reading documents, writing a letter)

16. The task requires working with image/video data or might require working with image/video data in the future:

1: Task does not require looking at images or videos, or otherwise using your eyes (e.g. having a phone conversation)

3: Task may occasionally require utilizing images and video (e.g. greeting customers, knowing whether you're alone before entering a password)
5: Task requires analyzing images and videos (e.g. finding defects in products, looking at surveillance footage, classifying objects in pictures, facial recognition)

17. The task requires working with speech data or might require working with speech data in the future:
1: Task does not require listening to or communicating with speech (e.g. independent tasks such as lifting objects, repetitive assembly work)
3: Task may require occasional listening, talking, or communicating (e.g. construction work, being a cashier, financial analyst)
5: Task requires heavy speech processing, or communicating with speech (e.g. telemarketing, translating between languages, giving a speech, having a conversation)

18. The task requires working with other types of data (other than text, image/video, and speech):
1: Task does not require working with digital data in any form (e.g. making handmade art)
3: Task requires working with some types of data at a low frequency (e.g. performing restocking tasks at a grocery store, testing machines for maintenance)
5: Task requires constant interaction with machine or sensor data. (e.g. monitoring temperature/weather, analyzing pricing data, monitoring machine performance)

19. Many components of the task can be completed in a second or less
1: Task takes a long time to complete (e.g. making a plan, writing a book)
3: Task cannot be done instantly, but also does not involve much long-term planning (e.g. performing a surgery, delivering food)
5: Task can be done instantly, or can be broken up into smaller choices that can be done instantly (e.g. Identifying a picture)

20. Each instance, completion, or execution of the task is similar to the other instances in how it is done and these actions can be measured
1: Task primarily involves rare or unique situations that cannot be summarized easily with machine-readable data (e.g. making strategic decisions for a company)
3: Data can be collected but the data output structure is highly varied (e.g. performing different types of surgery will generate different kinds of feedback)

5: Data are already available or can be easily collected (e.g. customer service transcripts, text translation, image classification, stock price movements)

21. Actions in the task must be completed in a very specific order, and practicing the task to get better is easy

1: Task involves many rare-occurring or unique situations that make the task hard to practice (e.g. therapy, negotiating)

3: Task involves some components for which a reward function can be defined (e.g. shipping/receiving in a warehouse, designing mechanical components)

5: Sequences can be repeated and tested over and over again, and there are "right" moves that can be used to generate rewards (e.g. video games, industrial process optimization, investment decision-making)