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Hacking the venture industry: An Early-stage Startups Investment framework for data-driven investors

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ABSTRACT

Investing in early-stage companies is incredibly hard, especially when no data are available to support the decision process. Venture capitalists often rely on gut feeling or heuristics to reach a decision, which is biased and potentially harmful. This work proposes a new data-driven framework to help investors be more effective in selecting companies with a higher probability of success. We built upon existing interdisciplinary research and augmented it with further analysis on more than 600,000 companies over a 20-year timeframe. The resulting framework is therefore a smart checklist of 21 relevant features that may help investors to select the companies more likely to succeed.

1. Introduction

With the democratization of infrastructure services and the proliferation of low-cost technology stacks, over the last few decades, it has been relatively easy to transform an idea into a proper company. However, the innovation boost generated by those companies has demanded a huge amount of support capital. This capital, although theoretically available and highly mobile, has not fit the risk profile that most of the traditional funding institutions could bear, and required the introduction of a new player in the market.

This new player is called a venture capitalist (VC). A VC is, in fact, driven by a completely different risk-return profile, and she often backs companies that would not be supported otherwise. As Ewens et al. (2018) showed, technological shocks (i.e., the introduction of Amazon Web Services) have lowered the cost of initial experiments and therefore increased the value of real options making it possible for VCs to fund these types of risky projects.

The VC game is a high-risk high-return one, driven by a power law distribution and an incredibly high failure rate. In fact, a VC always needs to pursue companies that can grow and scale at a stellar speed, but that, for the same reason, could fail overnight. Even if this model is highly inefficient, it is not even yet clear whether a different one is viable or conceivable (Neumann, 2019).

Nonetheless, over the last fifty years, the industry has gradually grown to be worth tens of billions, and the success of the so-called 'unicorns' (i.e., companies that received $1B+ in funding) has made the venture capitalists stars and also being an entrepreneur a respectful career option.

In reality, only a few companies and very few funds achieve impressive results, while the vast majority fail and do not even return the money to their original investors. To an investor, this can be attributed to two different issues: an *identification* problem – a poor ability to identify the rights deals – and a *mispricing* one (paying too much for what the company is potentially worth).

The mispricing problem is a very serious one. Gornall and Strebulaev (2020) recently showed that most of the investments done by VCs are completely detached from any fundamental, and often can be overvalued up to 100% of their real value. This is mainly due to a lack of quantitative robust valuation methods that can help to assign the right price to an early-stage company. Methods that are normally used by later-stage investors (e.g., private equity investors) to evaluate companies often relies on fundamental approaches to compute a Net Present Value (as for example in the Discounted Cash Flow). Early-stage venture capitalists and business angels (BAs) must turn instead to other techniques, such as the Scorecard, Checklist, or VC method, because many of these data points are merely projections and the time series are not long enough.

The identification problem is as much relevant as the mispricing problem but solved by every different investor through heuristics. Gut

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feeling is what almost every early-stage investor relies on, which is nothing more than pattern recognition based on previous experiences.

It comes without saying that this is inefficient and based on several myths that every investor thinks to be truth in stone (e.g., not funding companies where the co-founders are relatives). Even though heuristics and gut feelings usually do the job, a statistical or quantitative approach could prove to be more useful. Humans, in fact, tend to generally have problems in processing large amounts of data, as well as dealing with sample selection bias, data truncation or invalid information, and all sorts of biases ranging from hindsight to confirmatory to overconfidence (Astebro & Elhedhli, 2006). Furthermore, it has been proven that human heuristics fail and under-emphasize cognitive-demanding elements (Catalini et al., 2018) and that models that are created to maximize financial success outperform models trained to mimic human evaluators, clearly identifying an opportunity for quantitative approaches in venture capital. In other words, machines can do the VC job fairly well and this theoretically justifies the rationale of our study. Hence, the goals of our work are to debunk some of those myths and provide early-stage investors with a more quantitative-based approach to startup investments.

In order to achieve those goals, we use two instruments in our toolbox: first of all, we build upon good academic literature that stems from corporate finance as much as computer science. Second, we use machine learning and artificial intelligence to help VCs predicting the likelihood of startup success.

Even though a few attempts have been made to try to model the success of a company through time (Hunter et al., 2018), this represents a completely new approach. As a matter of fact, while hedge funds and investment banks have completely embraced the power of data analysis, VCs still remain anchored to the traditional way of sourcing, evaluating and closing deals. A few forward-looking investors are actively trying to incorporate machine learning into their workflows (we could not count more than twenty funds worldwide in this space — see Corea, 2019). Some of them are trying to use AI to find the right buyer, others to identify trends or competitors, others to match co-investors and deals. Regardless of the specific use case, they are using machine learning to become better investors and to shape their competitive advantage in an industry that is quickly saturating.

Our work contributes to this space by providing a new data-driven framework for investing in early-stage companies, identifying a set of relevant variables that could help an investor to take better decisions. The work fits a well-known stream of research that uses multivariate discriminant analysis (Wetter & Wennberg, 2009) to rank companies (e.g., Altman's Z-Score, ZETA method, etc.), but it suggests qualitative data as a valid alternative when financial data are not available.

The rest of the paper is therefore structured as follows: in Section 2 we discuss the main research question underlying the study and we place it in context to the existing literature. In Section 3 we show how we constructed the dataset and descriptive analysis, while in Section 4 we present the results of the empirical analysis. In Section 5 we discuss the implications of the work and finally, conclude in Section 6 proposing avenues for future research.

2. Previous literature and research question

The idea of understanding the determinants of company success is certainly not new. A large amount of previous literature exists on the topic, with a variety of different works that have tried in the past to identify specific variables that could explain, to different extents, the likelihood of a company to succeed or even to predict the probability of a person to pursue an entrepreneurial career (Ng & Stuart, 2016).

Da Rin et al. (2013) first tried to map in a detailed review all the themes related to the research in this field (a later similar review has been also done by Tykvová, 2018) and showed how a holistic approach to success prediction is, in fact, missing. Corea (2019) therefore identified three macro-groups of variables (and related studies) that could provide the theoretical and empirical base for this work.

First of all, a strong focus has been given throughout the years to the personal characteristics of the entrepreneurs who are starting the company as well as the team they build to run it. Starting from basic demographic features, people in their 30 s (and in particular male that scored highly on ability tests) or early 40 s (Azoulay et al., 2020) are more likely to succeed (Frick, 2014; McKenzie & Paffhausen, 2017; McKenzie & Sansone, 2017; Wadhwa et al., 2008). A different age indicator could be obtained through the years of experience, which usually averages at least 8 years after college (Ng & Stuart, 2016). Ethnic similarity and the graduation from the same top universities of an investor increases the likelihood of receiving funding (Bengtsson & Hsu, 2015; Sunesson, 2009), and being married/cohabit is positively associated with a higher probability of success (Miettinen & Littunen, 2013). Investors suffer from a strong similarity bias as well, which brings them to invest not simply in entrepreneurs with similar educational and professional background, but also means that if they are used to work with startups they will overlook an entrepreneur's previous track record in a big corporate context and vice-versa (Franke et al., 2006).

Contrarily to what publicly thought, being previously unemployed (Miettinen & Littunen, 2013) or being an unsuccessful serial entrepreneur (Gompers et al., 2010) do not result in a higher success rate, but only having successfully started and run a company before does (Gompers et al., 2010). Successful serial entrepreneurs also get better valuation (Hsu, 2007) and are on average better in timing the market, i.e., they are better at selecting the best moment to start a company (usually during market booms, according to (Ng & Stuart, 2016)) and the industry where to focus. Even possessing an MBA seems to be detrimental (Hoberg et al., 2009).

If it is also true that preparedness matters more than passion (Chen et al., 2009), the common myths around the ideal entrepreneur need to be given a second thought. In fact, from a psychological point of view, previous studies show that grit (i.e., perseverance towards long-term goals) is a powerful attribute to look at in a founder that is related to her probability of succeeding (Mueller et al., 2017). The same is also true for resilience, which is defined as hardiness, resourcefulness, and optimism (Baum & Locke, 2004), for the need for achievement, and for whether the entrepreneur has an internal locus of control, i.e., the subjective perception of own capacity to control events (Ayala & Manzano, 2010, 2014). Souitaris and Maestro (2010) have shown instead, counterintuitively to common sense but according to the need of a new technology ventures, that top management team polychronicity (i.e., engaging in multiple tasks simultaneously or intermittently and believing this is the best way of doing things) is positively correlated with the financial performance of the company. Social networks and relationship capital have also a strong impact on the ability to both raise funding and the probability of success. Shane and Stuart (2002) showed that having direct or indirect ties with reputable VC investors improves the entrepreneur's fundraising ability, and getting a lower valuation from highly reputable investors is usually preferred to the opposite situation (Hsu, 2004). Liang and Yuan Soe-Tsyr (2013, 2016) reached a similar conclusion, in the situation provided that not too many other investors are connected to the company as well (in other words, that not too much competition exists around a specific deal).

On the same line of research, Gloor et al. (2011, 2013) found evidence that centrality to a network increases the chances of an exit: a strong and robust professional network (Nann et al., 2010) has indeed a positive effect on fundraising ability (Banerji & Reimer, 2019) and on the performance in the first four years of a company development. A personal network starts becoming more relevant later along the growth of the company (Littunen & Niitykangas, 2010). Sharchilev et al. (2018) provided instead evidence for a "wisdom of the crowd" paradigm. The authors use open sources to predict the likelihood of receiving further funds and they show that online mentions play a big role in building the company's perception in the eyes of future potential investors.

The way in which an entrepreneur assembles a team is also incredibly valuable in the effort of identifying the variables of success. Mueller and Murmann (2016) found indeed that a mix of business and technical skills is paramount, and has a positive impact on company performance when the founder has a technical background. Eesley et al. (2014) investigated the composition of such a team concluding that diverse teams exhibit a higher performance only in competitive commercialized environments. In markets where a cooperative commercialization environment is instead required and new innovation strategies pursued, a strong technical team is much more effective than a balanced one. The team has to be complete though and heterogeneous (Jin et al., 2017). Furthermore, the entrepreneur who started the company is not always the same one that keeps running it, and the role is often filled by a more experienced manager to improve the overall performance (Ewens & Marx, 2017).

Although not confirmed in academic literature, practitioners' studies (First Round Capital, 2015) show that gender diversity has a positive impact on the probability of success: in fact, having at least one female co-founder seems to be associated with higher performance and probability of exit.

Finally, other correlations may be found in several studies, although some of them are counterintuitive or hard to explain, as for example the positive impact of calling a company after the owner name (Belenzon et al., 2017; Guzman & Stern, 2014, 2015, 2020).

A completely different set of predictive variables can also be drawn from the financial aspects of the company.

Several studies showed that VC-backed companies are more likely to exit through an IPO or an acquisition (Bertoni et al., 2011, 2013; Hoberg et al., 2009; Hsu, 2006; Inderst & Mueller, 2009; Puri & Zarutskie, 2012; Ragozzino & Blevins, 2015), especially if the VC has a strong reputation (Chemmanur et al., 2011; Gulati & Higgins, 2003; Nahata, 2008; Ozmel, Reuer et al., 2013; Sorensen, 2007) and has backed a company that IPO-ed as one of the first five investments in her portfolio (Nanda et al., 2020). This effect is also stronger for VCs with previous experience in either VC or startups (Zarutskie, 2010), or high specialization (Gompers et al., 2009; Hull, 2018). Angel investment and early-investor support seem to also improve the likelihood of growing and exiting (Kerr et al., 2014; Lerner et al., 2016), although this conclusion is not widely accepted (Cumming & Zhang, 2018; Nahata, 2008; Nahata et al., 2014). Ewens and Rhodes-Kropf (2015) also suggested that there is a performance persistence in VC's general partners as well as a preferred way of exiting companies of the portfolio, i.e., if the partner has created the conditions for an acquisition she will continue to do so, while if an IPO has been historically the preferred exit path, she will keep bringing companies to the public market.

Even the deal structure has a relevance for success likelihood, and in particular it depends on equity share (Miettinen & Littunen, 2013), whether the company has received funding through convertibles notes (Cumming, 2008), debt (Cole & Sokolyk, 2018; Robb & Robinson, 2014), if the deal has been syndicated (Das et al., 2011; Tian, 2011), whether the company has been able to raise an interest of at least €75,000 (Groenewegen & de Langen, 2012; Lasch et al., 2007), as well as the degree of control rights VCs ask for (Cumming, 2008). This last aspect is stronger if they have the right to replace the CEO and own the majority of the board seats.

Furthermore, a last group of studies can be observed through a business/operational lens. First of all, the number of patents is positively related to the likelihood of exiting (Cockburn & MacGarvie, 2009; Hsu & Ziedonis, 2011; Mann & Sager, 2007) and in general to the chances of getting funded (Baum & Silverman, 2004; Farre-Mensa et al., 2020; Haeussler et al., 2014; Lahr & Mina, 2016; Zhou et al., 2016) at a higher valuation (Greenberg, 2013). The same is true for government research grants (Islam et al., 2018), which increases the likelihood of funding in the six months after the grant (and the effect is stronger if the company has few or no patents at all), and being part of an acceleration program (Plummer et al., 2016). Strategic alliances (Baum & Silverman, 2004; Hoenig & Henkel, 2015; Lindsey, 2008; Ozmel, Robinson et al., 2013) and a board composition with no more than two VCs (Coats, 2018) also have a positive correlation with exit rates.

Miloud et al. (2012) found that higher product differentiation, industry growth rate, completeness of the management team, number of founders, number of alliances, and previous industry/management/startup experience (Azoulay et al., 2020; Chatterji, 2009) of the founders have a positive impact on the probability of fundraising and receiving a higher valuation.

More complex models with up to 26 different business variables have been created for different markets (Lussier & Halabi, 2010; Teng et al., 2011), also showing that clear financial and accounting information, an adequate working capital, strong marketing capabilities (Song et al., 2008; Zhao et al., 2012), as well as professional advice (Marom & Lussier, 2014) increase the probability of a company to exit successfully. Another 22-variables model has been proposed by Kirsch et al. (2009), where they concluded that (complete) business plans are not always required in order to raise funding, while prior entrepreneurial experience and team characteristics are somehow relevant. Finally, Catalini et al. (2019) confirmed previous findings that there is, in fact, a positive correlation between the likelihood of receiving funding and features such as being registered as a corporation, being incorporated in the US state of Delaware, having a short name, or having filed patents/trademarks. Similar results have been previously proposed by Guzman and Stern (2020) but in relation to the company's growth rather than funding.

In Table 1, we summarize all the relevant features that can be used to predict, respectively, the likelihood of success of a company ("*direct impact*"), the probability of receiving funding ("*indirect – deal formation*"), and the likelihood of having a higher valuation with respect to the market peers ("*indirect – valuation*").

The rationale for this deep scan of previous studies and analyses is for us to have a baseline to build incrementally a new model that allows for a more objective investment decision process. In fact, the main research question we are trying to address is whether an optimal way to evaluate startups investment potential exists, and if so, what is it.

We know that directly embedding heterogeneity is fundamentally a measurement problem (Catalini et al., 2019; Hathaway & Litan, 2014), but we also know that a wide spectrum of signals has some individual predictive power for the likelihood of success of a company. We also acknowledge that existing variables and methods do not yield clear-cut answers, as well as the fact that industry practitioners prefer to follow experience, gut-feeling or more traditional approaches to reach a decision on whether to invest or not.

Therefore, our intent is to build up a new framework starting from individual variables already shown to have a predictive power in previous literature and practice, and augment it through a data mining approach. We believe this approach may mitigate the use of intuition in investment decisions and provide a more fair and transparent funding process for entrepreneurs.

3. Data and descriptive analysis

As already mentioned in Corea (2019), the traditional investment process of an early-stage investor is slow, inefficient and often emotionally-driven (Sheehan & Sheehan, 2017). Creating an unbiased and de-risking selection method could, therefore, prove to be beneficial both for business angels as well as VCs. However, a series of structural issues need to be solved first.

The first issue in this class of studies is the inaccuracy and lack of data. A centralized, public and shared repository of verified data

Table 1
Taxonomy of signals able to predict the likelihood of success of a startup.

Impact	Variable	Reference	Effect
Direct Impact	Track record	Gompers et al. (2010); Hsu (2007); Lafontaine and Shaw (2016); Kirsch et al. (2009)	Previously successful entrepreneurs are more likely to succeed, especially if they previously worked for an incumbent in the same sector (Chatterji, 2009)
	Patents	Cockburn and MacGarvie (2009); Mann and Sager (2007); Hsu and Ziedonis (2011); Baum and Silverman (2004); Zhou et al. (2016); Haeussler et al. (2014); Farre-Mensa et al. (2020); Lahr and Mina (2016); Greenberg (2013); Guzman and Stern (2020)	The higher the number of patents, the higher the likelihood of exit (and in general, this increases the likelihood of getting funded and receiving a higher valuation).
	Trademark	Guzman and Stern (2020)	Companies with trademarks are more likely to grow
	Investors' Brand	Hsu (2006); Nahata (2008); Gulati and Higgins (2003); Chemmanur et al. (2011); Ragozzino and Blevins (2015); Ozmel, Reuer et al. (2013)	Having been financed by more reputable VCs increases the likelihood of exits and faster growth
	Control Rights	Cumming (2008)	Stronger control rights (i.e., drag along, redemption, antidilution, majority votes, majority boards, CEO replacement) increase the likelihood of success, and in particular the power to replace the CEOs as well as owing the majority of the board seats
	Convertible Notes	Cumming (2008)	An acquisition is more likely (and IPO less likely) if convertible notes are used
	Debt	Cole and Sokolyk (2018); Robb and Robinson (2014)	Firms using debt are more likely to survive and achieve higher revenue
	Strategic Alliances	Lindsey (2008); Hoenig and Henkel (2015); Baum and Silverman (2004); Ozmel, Robinson et al. (2013)	Strategic alliances associated with higher exit
	School	Sunesson (2009)	Exit likelihood increases if the VC and entrepreneur went to the top 3 schools
	Syndicate	Tian (2011); Das et al. (2011)	Syndicate deals are more likely to exit at a higher value
	Professional Advice	Marom and Lussier (2014)	Higher likelihood of success if the company has professional advisors
	Team Diversity	Eesley et al. (2014); Jin et al. (2017)	Diverse founding team (in terms of human capital, skills, experiences) exhibits higher performance if in competitive markets. However, the team has to be complementary
	Network	Gloor et al. (2011, 2013) Nann et al. (2010); Banerji and Reimer (2019)	If an entrepreneur has a strong network and is central with respect to that network, she tend to raise more funds and has a higher probability of succeeding
	Working Capital	Lussier and Halabi (2010); Halabi and Lussier (2014); Teng et al. (2011)	If a company has adequate working capital, it is more likely to succeed
	Accounting Information	Lussier and Halabi (2010); Halabi and Lussier (2014); Teng et al. (2011)	If a company has clear financial/accounting statements, it is more likely to succeed
	Parents	Lussier and Halabi (2010); Halabi and Lussier (2014); Teng et al. (2011)	If an entrepreneur has parents who were entrepreneurs, higher success
	VC Support	Puri and Zarutskie (2012); Sorensen (2007); Inderst and Mueller (2009); Nanda et al. (2020); Bertoni et al. (2011, 2013); Giot and Schwienbacher (2007); Hoberg et al. (2009); Chemmanur et al. (2011); Croce et al. (2013); Catalini et al. (2019); Ragozzino and Blevins (2015)	VC-backed companies are more likely to go public or to be acquired and less likely to fail (and grow faster)
	Founders Age	McKenzie and Sansone (2017) McKenzie and Paffhausen (2017); Azoulay et al. (2020); Wadhwa et al. (2008); Frick (2014)	Founders in their 30s are more likely to succeed (alternatively, 8 years of post-college experience)
	Marital Status	Miettinen and Littunen (2013)	If the founder is married or cohabit, this is positively correlated with the likelihood of success
	Previous Employment	Miettinen and Littunen (2013)	If the founder comes from being previously unemployed, there is a negative correlation with future success
	Founders Replacement	Ewens and Marx (2017)	If the founder is replaced with experienced managers, performance improves
	Equity Share	Miettinen and Littunen (2013)	The equity share, i.e. the capital owned by the entrepreneur as a percentage of total assets, is positively associated with the likelihood of success

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Table 1 (*continued*).

Impact	Variable	Reference	Effect
	VC Partner Experience	Zarutskie (2010)	If partners of a VC fund have prior experience either in VC or startups, they have larger and more exits
	VC Partner Specialization	Gompers et al. (2009); Hull (2018)	VC firms that are specialized in a few industries have more exits than generalist VCs
	VC Partner Exits	Ewens and Rhodes-Kropf (2015)	If a partner has done IPOs in the past, the likelihood of an IPO increases. The same is true for acquisition
	Marketing	Lussier and Halabi (2010); Halabi and Lussier (2014); Song et al. (2008); Zhao et al. (2012)	If the company has strong marketing efforts, it is more likely to succeed (especially if the founders have marketing experience)
	Gender	First Round Capital	Companies with at least 1 female founder perform better
	Board Composition	Coats (2018)	If the company has more than 2 VCs on the board, exits will be lower (controlled for investment stages, industry groups, and time periods). The same is true for a board with no VC
	Eponymous	Belenzon et al. (2017)	A company named after its owner has a higher probability of success (controversial though, according to Catalini et al., 2019; Guzman & Stern, 2014, 2015, 2020)
	Angels Support	Lerner et al. (2016); Kerr et al. (2014)	An angel-backed company is more likely to survive, grow, outperform and exit than its competitor. It also tends to grow in terms of employees and subsequent financing
	Industry Experience	Song et al. (2008); Miloud et al. (2012); Azoulay et al. (2020)	If founders have industry experience, there is a higher probability of success (and higher valuation)
	Grit	Mueller et al. (2017)	If founders show more grit (i.e., perseverance toward long-term goals), they have a higher likelihood of succeeding
	Resilience	Ayala and Manzano (2010, 2014); Baum and Locke (2004)	Resilience in founders (defined as hardiness, resourcefulness, and optimism) increases the likelihood of success
	Internal Locus of Control	Ayala and Manzano (2010)	Having a founder with an internal locus of control (i.e., the subjective perception of own capacity to control the events) is positively related to venture growth
	Need for Achievement	Ayala and Manzano (2010)	Having a founder with a deeper need for achievement is positively related to the venture growth
	Polychronicity	Souitaris and Maestro (2010)	Top management team polychronicity has a positive impact on financial performance
	Corporation Form	Guzman and Stern (2020)	Companies registered as corporations are more likely to grow
	Delaware Incorporation	Guzman and Stern (2020)	Companies incorporated in the US state of Delaware are more likely to grow
	Name Length	Guzman and Stern (2020)	Companies with shorter names are more likely to grow
	Minimum Investment	Lasch et al. (2007); Groenewegen and de Langen (2012)	Having raised more than €75,000 increases the probability of success
	Social Capital	Shane and Stuart (2002); Liang and Yuan Soe-Tsyr (2013, 2016)	If the entrepreneur has direct or indirect ties with a reputable VC, they tend to get funding easier
	Ethnicity/School	Bengtsson and Hsu (2015)	Similar ethnicity startup-VC or university increases the likelihood of investment
	Research Grant	Islam et al. (2018)	If the startup gets a government grant, the probability of getting a VC investment increases in the following 6 months and the effect is stronger if there are few or no patents
	Similarity	Franke et al. (2006)	Having a similar educational/professional background increases the likelihood of getting funded
Indirect Impact (Deal Formation)	Accelerators	Plummer et al. (2016)	Venture development organizations (VDO) and third-party affiliation increase the likelihood of getting funded

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Table 1 (*continued*).

Impact	Variable	Reference	Effect
	Online Mentions	Sharchilev et al. (2018)	Having more online mentions increases the likelihood to receive further funding
	Corporation Form	Catalini et al. (2019)	Companies registered as corporations are more likely to receive VC funding
	Delaware Incorporation	Catalini et al. (2019)	Companies incorporated in the US state of Delaware are more likely to receive VC funding
	Name Length	Catalini et al. (2019)	Companies with shorter names are more likely to receive VC funding
	Trademark	Catalini et al. (2019)	Companies with trademarks are more likely to receive VC funding
	Patents	Catalini et al. (2019)	Companies with patents are more likely to receive VC funding
	Reputation	Hsu (2004)	High-reputation-low-valuation VCs are preferred to low-reputation-high-valuation investors
Indirect Impact (Valuation)	Product Differentiation	Miloud et al. (2012)	The higher the product differentiation, the higher the valuation
	Industry Growth	Miloud et al. (2012)	The higher the industry growth rate, the higher the valuation
	Industry Experience	Miloud et al. (2012); Azoulay et al. (2020)	If founders have industry experience, the higher the valuation
	Management Experience	Miloud et al. (2012)	If founders have previous management experience, the higher the valuation
	Startup Experience	Miloud et al. (2012)	If founders have previous startup experience, the higher the valuation
	Founding Team	Miloud et al. (2012)	If the number of founders is higher than one, the higher the valuation
	Alliances	Miloud et al. (2012)	The higher the numbers of alliances, the higher the valuation
	Management Team	Miloud et al. (2012)	If the management team is complete, the higher the valuation
	Management Background	Mueller and Murmann (2016)	The company performs better if the management team is technical and employs business people, not the other way around

on startups does not exist, which makes any analysis very hard to be consistently performed. The data that are available through private platforms and providers is also often inaccurate because entrepreneurs are not correctly incentivized to share personal data and investors prefer to not give away their personal deal flow and information that represents their competitive advantage (Kaplan & Lerner, 2017). So, although data are sparse and incomplete, we decided to use Crunchbase[1] as the main source of data for this analysis. We also integrated with LinkedIn information where appropriate or missing from the Crunchbase dataset.

The second major type of issues is instead related to the effect of a VC investment. It is indeed very difficult to disentangle the intrinsic success features of a startup from the additional value a VC brings to the table. It is clear that an external investment is not the only determinant of success for a company, but it is by all means an accelerator, that can reduce the time-to-exit, and in general foster the development and growth of a business. In this study, we will try to mainly capture the set of features that are related to the company itself and proxy the additional value of an investment made by a venture capital fund through specific independent variables, without any particular emphasis on disentangling the two effects. Understanding the relevance of VCs in companies' growth would be, indeed, out of the original scope of this work.

The last point develops further the second one and concerns the definition of success: is a company that attracts external investment a success? Is a company that grows a successful company? What does success in this industry really mean? This builds upon a series of other intrinsic issues for the sector, as for example the lack of formal bankruptcy filings or the very long (usually between seven and ten years) time-to-exit, but it is certainly a point that causes controversy among different players. In general, we agree with previous studies (Meglio et al., 2016; Rosenbusch et al., 2013) stating that new ventures' performance is a multidimensional construct rather than a single unit of measurement.

We therefore decided to adopt different measures of success and test the models for each of those measures. Kerr et al. (2014) claimed that there are three measures of success: venture survival, venture growth, and venture financing. Lerner et al. (2016) expanded on those measures by including successful exits and employment growth. Similar measures (IPOs, acquisition, sales growth, and employment growth) are used in Azoulay et al. (2020) and Baum and Silverman (2004). We thus decided to use subsequent financing and potential exits, either through acquisition or IPO, as our dependent variables for this analysis. This decision has been motivated by three reasons: first of all, we are conducting this analysis wearing an investor's hat and therefore being interested in eventually returning money to the limited partners (either through an exit or a secondary market sale, which is made possible only by subsequent rounds of funding). Second, we found more evidence in the literature of studies that focus on these metrics rather than growth, so using the same measure of success makes our study more comparable and consistent with other works. Finally, the other measures (Davidsson et al., 2010) are not viable because of a lack of data (i.e., sales growth) or because they do not apply to companies that are lean-by-default and software-driven (i.e., employment growth), so even if they are theoretically meaningful, in practice they are hard to be pursued and used for the sake of this analysis.

The model is accordingly built by aggregating the different success outcomes (i.e., following rounds, IPOs, and acquisitions), and framed as

[1] Crunchbase is a platform for finding business information about companies. We obtained the data through an Academic License.

a binary classifier (i.e., any *successful events* versus *no events*). Indeed, we are not interested in a specific successful outcome, but having specified that success is a multidimensional construct made by three different measures, we only want to be able to understand whether a company will in fact hit one of those three milestones or not. The trade-off is clear: we are sacrificing some degree of details and potentially an investor's preference (one investor may prefer to exit through sales rather than an IPO) for the sake of simplicity, but we do not see any constraint to run in the future a different analysis to predict specific success outcomes.

Our final raw dataset contains about 623,232 companies, incorporated worldwide over the last 20 years (1999–2018). Consistently with previous studies, we then selected companies that were early-stage, i.e., companies younger than four years and that had not reached a series C round of funding. Working retroactively though can create a series of issues and suffer from different biases including amongst others the survival one (in fact, companies that are not successful may simply disappear from the platform). To fix this problem, we framed the problem using a two-periods approach: we only considered companies that were incorporated between 2011 and 2015 (and therefore still startups at the time) and ignored companies incorporated before or after those dates as well as companies that received a series C funding over that period. Then, we run our analysis on a following period of three years (from August 2015 to August 2018), which is the period where we were expecting successful events to happen and therefore a way to verify the predictive power of our independent variables (in the same fashion of a more traditional backtest). The choice of the initial 4-years and simulation 3-years windows is not random, but it is derived from the average time of exiting a general investment for a generalist VC (regardless of sector and geography), which is about seven years.

This reduced the number of companies under scrutiny to about 120,507. For those companies, we collected 105 variables between raw variables directly extracted from Crunchbase, new synthetic and dummy variables (e.g., *country* dummy variables or *sector* dummy variables), and cleaned the missing values. This dataset allows us to access data to be used as independent variables such as *country*; *age*; *social media presence* (presence of a *Twitter account*, *LinkedIn account*, *Facebook account*, an *email*, a *phone number*, or a *website*); *number of previous funding rounds* and their *amounts*; separated detailed information for the *last round of funding* (*type*, *amount*, *valuation*); *number of investors*; *number of investors in the last round*; whether the *investors were renowned* or not; *number of founders*, their *gender*, *education (*the *total number* of their degrees, and the *average and highest number*), and whether they come from *different countries*; *sector*; *description*; *geography*. These are the variables used to build upon the existing literature to create the investing framework.

4. Empirical results

Even though other studies have shown that it is possible to use neural networks to identify additional relevant variables (Ciampi & Gordini, 2013), the lack of full transparency over the process due to black-box algorithms concerned us. We found that tree-based techniques are quite successful for this specific type of research question (Bhat & Zaelit, 2011; Krishna et al., 2016). This is a subset of machine learning methods that basically construct decision trees either for classification or prediction problems, and that are simpler and more interpretable with respect to other techniques. If more than one decision tree is used, the algorithm falls into the ensemble methods category (e.g., random forests).

There is clearly a trade-off at play: exploiting the nonlinear approximations of neural networks would allow us to neglect the assumptions of linearity and independence intrinsic to a traditional default prediction model. Hence, we would not need to specify any functional form or any distributions *ex-ante*. The cost is, however, a lack of transparency for the decision-maker and the impossibility of understanding why the algorithm optimized the weights related to a specific feature.

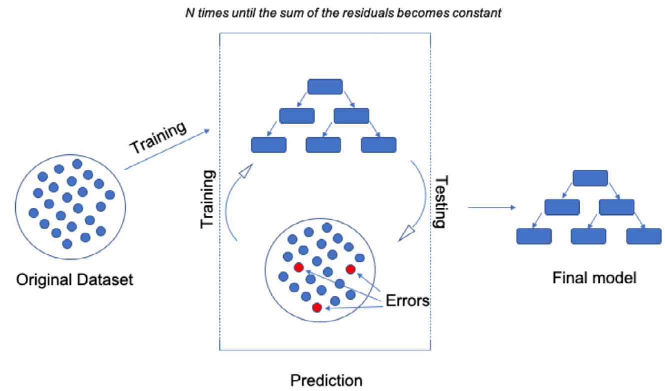

Fig. 1. Gradient Tree Boosting.

This is why we decided to use one of those ensemble methods, namely Gradient Tree Boosting (GTB), as our main classifier. GTB trains multiple trees on the original dataset and eventually uses a loss function to penalize the weakest predictions. The main idea behind it is using a weak learner method several times to get a sequence of different hypotheses that minimize the loss function. Previous studies (Arroyo et al., 2019), have shown that GTB seems to perform better than other tree classifiers and in line with other less transparent techniques (such as Support Vector Machine, for instance). In fact, it achieves a precision of overall almost 70% in predicting the company's success (intended as raising another round of funding, being acquired, or doing an IPO), which is quite remarkable for VC standards (Arroyo et al., 2019). This sets up GTB as the best method to be used to both achieve a high performance, as well as to be consistent and comparable with previous literature. Furthermore, GTB does not make predictors not independently but rather sequentially. The intuitive logic behind it is not far from a simple linear regression: it minimizes a loss function, but it does that by building a prediction base model first (even if it might be *weak*, i.e., slightly better than random) and then focusing on the data points that have been misclassified or difficult to analyze. The following steps try to include those data points into the base model and modify it accordingly until residuals can no longer be modeled (to prevent for overfitting). Hence, the model first is trained over a simple regression or decision tree. Then, the residuals are calculated and a new model is fitted using residuals as dependent variables and the same earlier inputs. This step is repeated multiple times until the sum of the residuals becomes constant (in other words, when the model starts overfitting — see Fig. 1).

The final model is therefore constructed by adding, step by step, weighted predictors to the base model through the following analysis on the residuals. This additive model is in fact quite powerful, and since it is constructed by sequentially using decision trees to embed more variables, it does not suffer from the black-box issues associated to other methods (e.g., neural networks). It also automatically returns, after *n* iteration, the variables that are relevant to explain a particular target outcome attaching a weight of importance to each predictor. To perform this analysis, we replicated the process used in Arroyo et al. (2019) to select features from the Crunchbase dataset. In Fig. 2, we show the results of this feature selection analysis, i.e., the first 50 features selected through the GTB (where the x-axis represents the relative importance of the features). It may be possible to plot more variables, but the predictive power decays as the number of variable increases, which is not meaningful for our analysis. As mentioned above, the GTB method incorporates features selection, which means that it is able to automatically provide a rank of the most relevant variables that are good predictors of the likelihood of company success. The goal of this analysis is not to double-check the variables that other studies already proved to be correlated with the success of a startup (although there are some in our dataset that correspond to other works), but rather to augment that list with something that has not been previously considered.

It is probably not so unexpected that companies in the USA and China have a higher probability of succeeding, but it is not so much for Sweden. We do not know whether this is due to a specific intrinsic skill that US and Chinese-based entrepreneurs have, for example, but we speculatively assume that having a strong and complete ecosystem may be as much important as having entrepreneurial skills. We could not test for this hypothesis, but this remains an interesting question for future works. The same is true for sector variables, where we found out that *Healthcare* and *Science and Engineering* are the most attractive and potentially rewarding sectors. Interestingly enough, *Software* or *Artificial Intelligence* do not have a probability of success as high as other sectors (e.g., *Energy*, *Transportation*, etc.).

Having a social presence has also some predictive power, whether it means having a LinkedIn, Twitter, or Facebook account, or a website, an email or a phone.

As we have already seen, the number of previous investors and their reputation matters, and so does it the presence of one or more angels in some earlier funding rounds.

Finally, the number of co-founders, their diversity in terms of gender and nationality, and their education can also be used as proxies of future success.

We clearly understand that some of these variables are merely qualitative and hard to justify and correlate with a higher probability of success, so we will consider them in the following section.

5. Discussion

We can now draw some conclusions from our investigation. We knew that humans have a systematic component of early-stage investing that can be identified and replicated (Catalini et al., 2018), as well as that those models trained to maximize financial outcomes outperform humans. Hence, we started this work building upon what has already been proven in the literature to have an impact on the likelihood of company success. We eventually tested for new variables, finding that some of them have different degrees of predictive power.

However, in order to create the final "Early-stage Startups Investment" (ESI) framework, we need to add a final ingredient: real investment constraints. We assumed at the beginning and throughout the entire work that having more information is, in theory, always better. This also applies in the venture capital space too, but it is constrained to the short decision timeframe, lack of data, and overall systemic complexity. Venture investors often need to move fast, especially at an earlier stage, and giving them too much information to gather and handle may end up having the opposite effect we wanted to have when we suggested injecting some analytics into the investment process.

Even if we mentioned above that machines can perform this prediction work as well as – if not better than – humans, we need to scale back our analysis to make it usable by people. Simple heuristics tend to perform better with respect to the ones that combine a large number of non-linear cues or that process complexity through statistically optimized weights. The "take-best" heuristic though seems too extreme for a complex environment as the VC industry is, and we thus prefer to work with a subset of cues.

In fact, Astebro and Elhedhli (2006) show how 21 is the optimal number of variables or clues one should consider when taking a decision. They tested different decision rules and heuristics to predict the commercial success of projects and concluded that experts use more information than what it is considered to be optimal. Hence, we think the framework should aim to contain that much information in order to allow VCs to process it on the fly. If we then consider the joint results of previous studies and our analysis, we find the following to be

Table 2
Early-stage Startups Investment (ESI) framework.

Framework	Max Score	
Founders Track Record	1	
Previously successful		*0.5*
Industry Experience		*0.5*
Previously unemployed		*−0.5*
Founders Count (>1)	1	
Founders Gender Diversity	1	
Founders Different Nationality	1	
Founders Marital Status	1	
Founders Age (30–45)	1	
Sector	1	
Deep Tech		
Healthcare		
Geography	1	
USA		
China		
Patents/Trademark	1	
Previous VC Funding	1	
VC Support		*0.25*
Convertible Notes		*0.25*
Reputable Investors		*0.25*
Syndicate		*0.25*
Previous Angel Funding	1	
Strong Control Rights	1	
Debt	1	
Advisory Team	1	
Team Heterogeneity & Completeness	1	
Board Composition	1	
More Than 2 Investors		*−0.5*
Social/Public Presence	1	
Marketing Capabilities	1	
VC Partner	1	
Specialized		*0.25*
Had Experience		*0.25*
Had Exits		*0.25*
Same School of the Founder		*0.25*
Strategic Alliances	1	
Driven Founder(s)	1	
Grit		*0.2*
Resilience		*0.2*
Internal Locus of Control		*0.2*
Need for Achievement		*0.2*
Polychronicity		*0.2*

a reasonable set of features an investor should look at when investing in early-stage companies.

In Table 2, we created a smart checklist for investors gathering all the information collected so far, i.e., a group of variables coming from the analysis of the previous literature as much as the data collected. The way in which we moved from the all-inclusive list of more than fifty variables from the literature to the other fifty from the data analysis is the following: we, first of all, eliminated all those variables with no direct impact on the likelihood of success. It can be proved that they have, as said, an indirect impact (e.g., being in an industry that grows fast increases the valuation, and a higher valuation could be associated to a higher probability of success), but this should be empirically tested, and thus they cannot be used for the purpose of this work. Then, we selected from the data analysis the variables that did not overlap with the literature review, such as the sector, geography, social media presence, etc. We eventually took out variables that we know to be unavailable to early-stage investors when approaching a company (e.g., working capital, accounting information, founder replacement, etc.). Finally, we grouped single instances of larger variables to create a more nuanced score. This leaves us with the 21 variables proposed in Table 2.

It is worth noting that most of the features presented in Table 2 concern the founding or management team, which is in line with previous insights (Bernstein et al., 2017). Even though some more complicated scoring systems may be implemented (Dixon & Chong, 2014), we created a very straightforward scoring system attached to

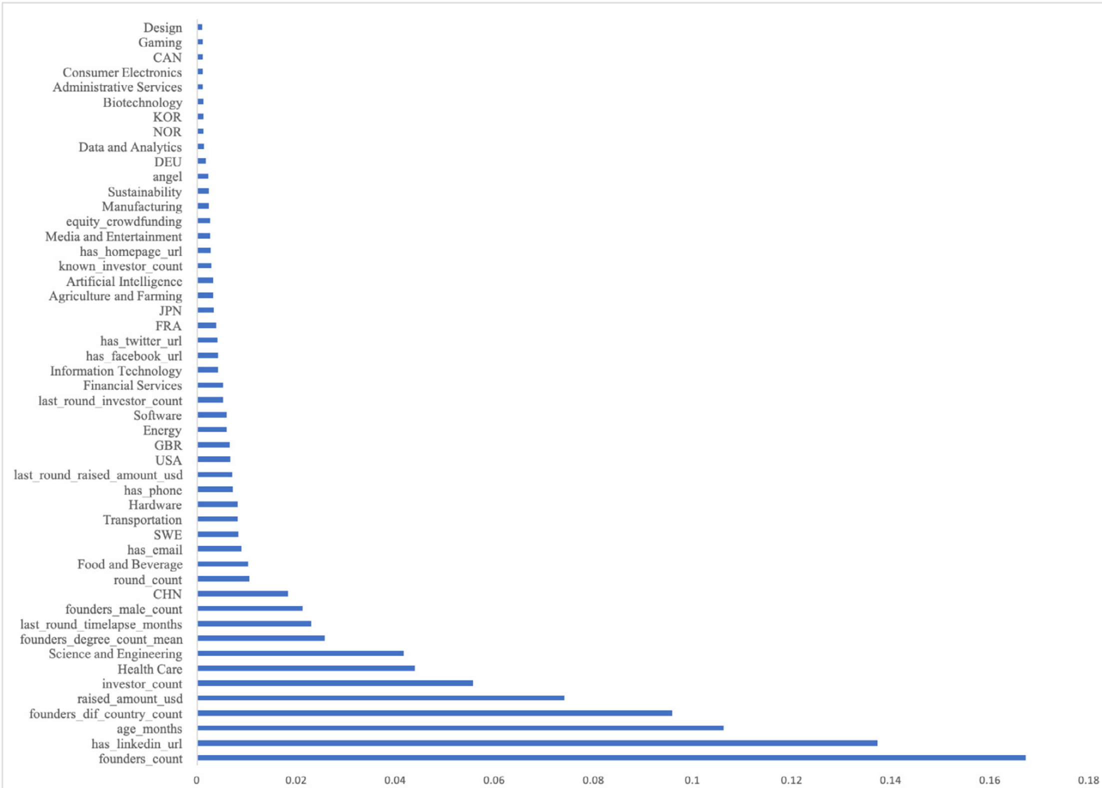

Fig. 2. Top 50 features selected.

the framework, which may help an investor to rate different startups and invest his limited resources only in the ones with the highest score. The system simply attributes a score of 1 if the company/founder checks the variable, 0 otherwise. We avoided however, to specify a minimum threshold for doing an investment, because this is related to the investors' risk profile as well as their opportunity to participate in a funding round. It is also impossible to use any pre-existing framework to rank such information given that all those variables are "*non-predictive*", i.e., not anchored on forward-looking assessments (Wiltbank, Read et al., 2009; Wiltbank, Sudek et al., 2009).

The idea of shaping the framework as a mix between a scorecard and a checklist finds evidence not only in the literature but also in industry. In fact, according to the Equidam Valuation report (2018), there are a few methods that are mostly used for startups' valuation, namely the Scorecard method, the Checklist method, the VC method, the Discounted Cash Flow (DCF) with Multiples and with Long-Term Growth (LTG). Each of those comes with advantages and drawbacks, and thus a weighted average of those five techniques is rather advisable, with weights that change depending on the stage of the company. This view is in line with ours as well the one proposed in Goldenberg and Goldenberg (2009), because it entails the idea of moving from a "real-option approach" to a "net present value (NPV) approach" for valuation. Where hard (financial) data are not available, it is necessary to base valuation on a more qualitative approach, but as the company matures you are able to gather more information and then move toward a more quantitative valuation approach.

The framework, therefore, proposes a strong influence of founders' characteristics, whether demographic (age, gender, nationality, marital status, number of cofounders), professional (track record), or psychological (grit, resilience, need for achievement, internal locus of control, polychronicity). On the same wavelength, other people-centric features that have a strong impact on the likelihood of success have been included in such a framework (team diversity and advisory team).

On an investment side, previous funding, strong control rights, the presence of company's debt, the composition of the board, and the choice of the VC to work with, are the second most relevant categories an investor wants to look at when considering a deal.

Finally, some operational-related variables have some impact as well (sector, geography, IP protection, public presence, and strategic alliances), but paradoxically these are less relevant than the previous two groups. Furthermore, it should be acknowledged that two variables (*sector* and *geography*), although relevant, are clearly contingent to the specific timeframe analyzed. Even though we are certain of the importance of the two features, we are also aware that the specific instances might in fact change in the future as the market evolves.

Before concluding this section, a few additional comments are required. The checklist proposed is based on firm-specific factors and does not prevent the investors from checking for market size, the type of problem the company solves, external factors (Tomy & Pardede, 2018), or doing due diligence on the technology, but it simply augments their capability to reach a decision with greater confidence.

Finally, we know that small investors often use the so-called "elimination-by-aspects" heuristics to select companies and exclude at a glance companies with fatal flaws (Maxwell et al., 2011). This list is an attempt to provide a holistic view of a company and avoid the circumstances where a company is rejected simply because of one missing variable. None of those variables is critical by definition, and there are always exemptions or counterexamples that can disprove the relevance of one or more of those variables (think of Zuckerberg and Facebook, or Gates and Microsoft, for example). This tool is an additional support for early-stage investing, and not a guarantee of success, and should be interpreted as such.

6. Conclusions

This study has attempted to unify the existing knowledge on how to effectively perform due diligence on early-stage companies by using analytics to augment some well-known results.

The generality of the framework makes it a powerful tool for VC investors to assess and evaluate companies in the initial stages of their lives. Its generality also makes it partially incomplete, because companies belonging to specific industries, adopting specific business models or using particular technologies may need further adjustments and variables to be taken into consideration. In fact, we believe the framework achieves a good balance between being general enough to allow investors to set a baseline for companies that deserve investment while and at the same time giving them room to improve it and personalize it as they wish.

The ESI Framework does not seek to be the only tool an investor should use in the decision-making process, but rather the first test for a potential investment. It does not help, in fact, to provide more intermediate feedback points or to shorten an investment exit time horizon, but rather, it helps to enhance the way capital should be (efficiently) allocated. Hence, an investor could refer to the framework to prioritize companies in her pipeline, or to operate a first filter in the inbound dealflow. In fact, large VCs normally receive between 2000 and 5000 investment proposals per calendar year, and this system may help them figuring out how to prioritize their time and optimize their processes. Moreover, we believe that every VC can select the risk-return profile that better fits her needs and strategy (and thus the corresponding score), but also that it might be possible to find an optimal threshold above which a company can be funded.

That being said in addition to being useful to single investors, the framework introduces opportunities for the entire industry: new superfunds are making the work of growth funds extremely hard, competitive, and less remunerative. This may push funds to change their strategies and look for companies at earlier stages before institution like the Vision Fund come in. The framework can in fact facilitate this transition toward earlier-stage investments.

Machine learning was not employed in our model to fully replace the job of any VC investor, but rather to augment their skills. Humans still have a relevant impact in what makes a business successful and in how to spot one that might become the next big hit, and we imagine that further studies may show the importance of creating hybrid human–machine models (Dellermann et al., 2017).

The rationale for this work was to demystify funding clichés and to help investors see past extreme risks, relying less on their gut-feeling and more on hard data. Gut-feeling is, in fact, an *intuiting process* (Huang, 2019) that can make you or break you (Huang & Pearce, 2015), and this is why having data supporting your initial thoughts is essential when it comes to investing in early-stage companies. In this paper, we decided to optimize the probability of success and identifying the determinants of success for a start-up. As mentioned in the introductory paragraphs, this is only one of the uses of machine learning in the venture space and of course does not guarantee that an investor gets access to the best deals. In fact, even having a perfect way to predict the success of a company, investors need to convince the best entrepreneurs to partner and work together, because money is most of the time only part of the additional value brought to the table.

This also creates a second interesting future avenue of research, which we previously identified to be a problem for the industry. We know that VCs influence the growth of a company (Croce et al., 2013) much more than banks (Cole et al., 2016), and the same is partially true for corporate venture capital (Colombo & Murtinu, 2017), but we do not know to what extent and in which way. It is of course incredibly hard to disentangle the different effects (Bertoni et al., 2011; Chemmanur et al., 2011; Croce et al., 2013), but investigating further the difference and the magnitude of the "*sorting* (or selection) effect" (cherry-picking skills) and "*treatment* effect" (providing better value-adding services) represents a future possible step (Sorensen, 2007).

Another interesting stream of research may interest the calculation of the optimal time-to-exit for a company. Intuitively, a VC would prefer the shortest holding period for any investment, but this is not true at all and actually holding periods shorter than three years might be harmful (Capizzi, 2015). This could be intrinsically connected to the probability of success of a company, so it may deserve further attention.

We are also aware that betting on the horse could be more rewarding than betting on the jockey (Kaplan et al., 2009). We believe our framework shows that people and team characteristics are extremely relevant (even more than pure business features) at the initial stage of development of a company, but we also intuitively think there comes a point where this may change. The study of this discontinuity, which also corresponds to the point where the valuation methods jump from the "real option" approach to an "NPV"-based one, has not been investigated yet and could provide investors with new insights.

The importance of the ecosystem is also paramount and usually not investigated in depth. Hong et al. (2018) show theoretically and proves empirically that a more competitive VC market both increases the likelihood of successful exits for low-quality projects and lowers the success for good companies. This implies that an ecosystem might indeed affect the probability of a company to be successful much more than traditional variables, and it might deserve additional attention. Moreover, it is known that public perception of a company (i.e., the words used to describe it in the news) can be used to augment the predictive power of the current methods (Xiang et al., 2012), although a causation study has not yet been performed on the topic.

Creating a structured model that emulates the investment decision-making process of a VC is also of interest. Many studies have tried different approaches, such as fuzzy theory (Afful-Dadzie & Afful-Dadzie, 2016; Afful-Dadzie et al., 2015; Aouni et al., 2014; Lin, 2009; Tian et al., 2018; Zhang, 2012), goal programming (Aouni et al., 2013; Colapinto & La Torre, 2015), or the Probabilistic Latent Factor model (Zhong et al., 2016), but the connection between those theoretical models and the probability of identifying a successful company still remains unexplored.

Finally, a component that is still weak and under research is the psychological one. We believe founders' (and VCs') personality influence the likelihood of starting a company and then make it a success (Kessler et al., 2012), and we are aware that some of the variables included in the framework are proxies of some personality traits. However, a more detailed analysis would bring more complete and useful information that could be used to understand whether the founder is a good fit for that specific project at that specific time. This concept could even be stretched to the point of trying to predict the right set of skills, personality traits, and inclinations that could make a person a better founder (Levine & Rubinstein, 2016; Ng & Stuart, 2016).

CRediT authorship contribution statement

Francesco Corea: Term, Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Giorgio Bertinetti:** Conceptualization, Validation, Supervision, Project administration, Writing - review & editing. **Enrico Maria Cervellati:** Conceptualization, Validation, Supervision, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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