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Business Valuation in the Face of Information Scarcity: A Synthesis of Methods and Adaptive Perspectives

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***Abstract*—**Valuations of unlisted companies are difficult because of unlisted company financial disclosures, comparable-company information and unlisted company transaction information can not be complete, outdated and it is difficult to find and verify company relevant information. Traditional methods like Discounted Cash Flow and market multiples approach remain effective but the accuracy is highly dependent on that assumption and evidence may not be equally accessible for every company. Machine learning can facilitate valuation by detecting financial market patterns, but the predictive models are unreliable when observations are scarce or not well matched to the focus company. Research on stochastic valuation further reveals that the form of distribution of a point estimator may be concealing important uncertainty. This paper overviews research on discounted cash flow valuation, enterprise valuation based on machine learning, private company comparable and uncertainty modeling. Based on the overview it then develops a conceptually Information-Scarcity Adaptive Framework (ISAV) where the type, aggregation and reliability of evidence guide the choice and reporting of valuation methods. Precise estimation is not intended. Instead, the framework is designed to assist transparent method selection and presentation of valuation ranges.

Contents of the framework involve steps like collection and verification of data, evaluation of financial statements and quality of data, selecting the suitable method, carrying out the valuation estimate through DCF, comparable multiples and machine learning when sufficient evidence is available, followed by estimate reconciliation, uncertainty analysis and transparent reporting. What makes this framework unique, is the introduction of an Information Completeness Score (ICS) which provides an initial indication by indicating whether the data is of high, medium or low quality, indicating to the analyst if more validation is needed before the valuation. ISAV framework also encourages explicit quantification of an estimate range to generate transparency about uncertainty, instead of providing a single valuation estimate as if it were exact. The article discusses the application of this framework to unlisted firms in India and the challenges faced owing to paucity of available data, while acknowledging that further empirical testing will be required to establish whether the framework delivers its promises in practice.

Keywords*—unlisted companies, enterprise value, information gaps, Information Completeness Score, explainable AI discounted cash flow, machine learning, valuation uncertainty*

INTRODUCTION

Valuations of companies are important to corporate decision making as they are used to help identify the best targets for mergers and acquisitions and investments; assess the feasibility of financing and risk; and assist to develop corporate strategy and planning. For listed companies, daily market prices and their financial reports also offer some precious information of their value. However, value estimation of non-listed companies is not always easy and demands that assumptions are made which are sometimes hard to verify.

The DCF method is one of the most frequently applied methods for valuation of a company, as it estimates the present value of the foreseeable cash flow to be generated by a company in the future. By discounting the future cash flow, investors get an indication of the worth of the company today, but the valuation can fluctuate a lot, depending on the assumptions made for the future cash flows and the applied discount rate. In the research of Vayas-Ortega et al. an entirely reliance on historical financial data was inconsistent in delivering valuations aligned with market expectations across different sectors, regions and periods [1]. In their follow-up study, the researchers tested out a variety of machine learning techniques and found financial attributes to be essential when attempting to predict value, yet the introduction of contextually relevant external factors was helpful in further optimizing the prediction accuracy. However, the practicality of the different methods would depend on the scenario and the condition in which the model was applied [2].

Various research papers addressed the different aspects of a company's valuation. Ernst investigated how simulation-based approaches can be applied to incorporate risks specific to a company for the purposes of estimating its business value [3]. Zhang et al.studied the application of machine learning techniques to predict the valuation of entrepreneurial companies in cases where data on financing is relatively limited and unevenly available [4]. Geertsema and Lu studied the application of machine learning techniques for relative valuation that allows the selection of the right combination of weights for peer companies[5]. Similarly Jagrič et al.studied the effectiveness of artificial intelligence algorithms for the identification of suitable peer companies when valuing private companies using market multiples [6]. Other papers dealt with specific challenges in valuation. El-Al, Galil and Gavious analyses how bias in markets and investors and their expectations influence company valuation [7]. Mohan, Bharathy and Jalan reviewed several approaches of valuing enterprise data and showed the importance of quality of data and its context [8]. Abideen and Wu examined the influence of investor sentiment and applied machine learning approaches to forecast company valuation [9]. Although all these papers shed light on specific issues in evaluating unlisted companies, none of them defined a coherent framework in which performance of

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available information is used to choose the most appropriate valuation method.

This indicates that this is not a problem of not having valuation techniques, but rather a question of how a decision-maker would reasonably adopt a technique when evidence is not full and valid. The paper surveys and assesses relevant literature and suggests a theory of valuation for unlisted companies, and especially for Indian companies. The work's contribution lies mainly in its theory-building quality, as it integrates and synthesizes various previous research and pinpoints the directions for future empirical research.

The three research questions have been formulated in this research:(1)What are the information quality problems regarding the valuation of unlisted companies?(2)How do current valuation approaches take invaluable evidence and/or incomplete evidence into account?(3)How can information quality assist in the process of choosing different valuation approaches as well as in explaining and assessing the uncertainties. Its contribution is literature-based and conceptual; it does not claim that the framework has been empirically tested or that the literature has been exhaustively reviewed.

LITERATURE REVIEW

Discounted Cash Flow Valuation

The most common technique of valuation used to estimate a target company's intrinsic value is applying Discounted Cash flow (DCF) method, which involves estimating the cash flows a company would generate in the future and calculating the present value of those cash flows. This technique provides valuation with the current market value of the company. However, the final result of this calculation is sensitive to changes in the assumptions made about future cash flow and discount rate; even small modifications in assumptions can change the value of the estimate. While DCF is a widely used valuation method, prior research suggested the DCF result can vary significantly among different sectors, regions, and markets, which points out that inaccurate assumptions can produce untrustworthy DCF valuations of targets. Vayas-Ortega et.al has used several estimates, such as cash-flows and discount-rate, to test the valuation models accuracy with the data from 42 companies in five sectors across five regions. Their results reveal that financial statements alone are unable to generate valuation estimates which are consistent with market valuing expectations. The research also shows the use of external information and data-driven processes improve the accuracy of some estimates [1]. They conclude that the reliance on historical and company-specific information is unable to generate consistent valuation estimates and identify the need to analyze the quality of available information and assumptions when applying the DCF method.

Machine Learning for Enterprise Valuation

Machine learning is a popular way to estimate a company's value because it can help to find the pattern in financial data and explains how different factors influence a company's value. Vayas-Ortega et al.evaluated18 machine learning techniques and found that bagging trees, support vector regression, and Gaussian process regression all performed well in their experiments. Their study also showed that the industry-specific and country-specific data could be used to improve the accuracy of the result [2]. Zhang et al.surveyed machine learning for valuing entrepreneurial firms, where information asymmetry and financing characteristics can influence the data that is available [4]. Geertsema and Lu studied the application of machine learning in relative valuation and peer weighting [5], while Abideen and Wu looked into how the investor sentiment could be used as an additional feature to improve the accuracy of forecast for company valuation [9]. However, these models' performance depends on the available data and the company being valued. The same model that performs well for one group of companies doesn't necessarily perform well for others, especially when valuing private companies. The accuracy also relies on how much training data you have, the differences in the companies' available data set and the target company, and the accuracy of the valuation records.

Comparable companies and Private Market evidence

Comparable companies and Private Market evidence Related-companies analysis and transaction-multiple are the most widely used approaches for estimating a company's value by analyzing the valuation of similar companies in the past or recent market transactions. However due to the widely used nature of approach their reliability depends on the availability of comparable firms and relevant transaction data and market conditions - which can be quite hard to achieve, especially when valuing private market companies. According to Selvam and Whittaker market transaction data is limited, inconsistent and suffers from potential bias; and transactions in private markets occur rarely and individual company differences make it hard to establish reliable valuations standard[10]. Geertsema and Lu explored whether machine learning can aid relative valuation by providing a better selection and weighting of comparable companies [5]. And also, Jagrič et al.have investigated the use of artificial intelligence in searching peer groups for private companies market multiples valuation [6]. In such a way, having market access doesn't necessarily mean getting an accurate valuation. Time and relevance of the information are no less important for the receiving of the realistic valuation.

Modelling Valuation Uncertainty

While so to say a traditional valuation can sometimes produce a number that easily deludes the sign requirement in the sense that it is very sensitive to the assumptions made with regard to future prospects of performance and other financial data thus not necessarily a straightforward exercise. Valacci et al. have suggested a stochastic DCF approach of estimating the fair values as a distribution[11] instead of a single figure to overcome such problems. Their method accounted for revenue trajectories and interrelations between balance items of a firm. While their study was based on the publicly traded corporations in the US and making its direction application less direct to private firms due to their unavailable data and disclosure, their research demonstrates an important idea that uncertainty can and should be included in valuation.rather than providing a number that is very specific and certain, analyst could offer

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more meaningful and realistic evaluation by acknowledging the degree of uncertainties that could not be excluded in finance.Likewise, Ernst used computer simulation to incorporate specific risks and uncertainties to business valuation of independent companies [3]. Those further studies need to examine the effectiveness of such approaches to private companies where the data is limited and unreliable.

CRITICAL ANALYSIS OF EXISTING APPROACHES

The literature study review demonstrates that not one valuation approach fits all situations. Each approach has its own complement and restrictions that relate to the information source and context Vayas-Ortega et al. [1] investigates how historical model accuracy and assumptions for discount rate help forecast cash flow valuation. In their later research, machine learning methods can improve valuation forecasts in certain circumstances, although the performance may differ across firms [2]. Ernst [3] studied another approach called simulation-based valuation accounting for risk factors unique to each firm. Zhang et al. [4] focused on machine learning models for entrepreneurial firm valuation;Geertsema and Lu [5] looked into the application of machine learning to relative valuation and how it enhance weight selection; and Jagrič et al. [6] explored the potential of artificial intelligence to find suitable peer groups in private-company valuation. El-Al et al. [7] raised the effect of valuation bias and market understanding, Mohan et al. [8] pointed to the need for sufficient data sources and context, and Abideen and Wu [9] considered how investor sentiment can be added in machine learning models to predict firm valuation. Furthermore, Selvam and Whittaker [10] considered challenges faced using private-market evidence, while Bottazzi et al. [11] demonstrated how valuation results can be converted into probability distributions and not single-point estimates.

All three are consistent and seem to complement each other in offering different insights. DCF models get to the heart of the issue, by requiring explicit assumptions and creating a clear relationship between a company's future cash flows and its value. But even minor variations in assumptions about growth or the discount rate can produce wide variations in valuation. Methods based on comparable-company and transaction multiples can give a market touchstone, but only if truly comparable firms exist and if recent transaction evidence exists.Machine learning techniques can identify complex patterns in data sets and produce data-driven valuation estimates. The accuracy of their predictions, though, ultimately rests on the quality and quantity of the training data, the extent to which information about the target company is available and the degree of similarity between the target company and the sample of companies used to train the model. Simulation- and probabilistic-based approaches also provide a useful way to model and communicate uncertainty; the accuracy of their predictions, though, depends on the evidence and assumptions underlying them.

Another important distinction is between business uncertainty and information uncertainty. Business uncertainty is concerned with the fact that a company's future is inherently uncertain e.g. demand for its products, pressure from competitors, cost of production, and other factors affecting its future cash flows. Information uncertainty, however, is caused by the limited availability of the evidence upon which the analyst makes his decisions e.g. missing financial statements, a lack of up-to-date disclosures, limited trading data, inappropriate comparables, and so on, or the lack of trust in the quality of the information source. While they are interconnected, and can affect each other, they are distinct types of uncertainty. A large valuation interval, for example, could be due to actual business uncertainty, or due to a lack of good information.

In sum, the studies reviewed here justify the consideration of information quality as an explicit criterion of value. Nonetheless, these studies do not imply that this issue has been overlooked. Instead, they suggest that information quality has been addressed in a roundabout way by multiple valuation approaches. We therefore propose the Information-Scarcity Adaptive Valuation (ISAV) framework as a first attempt at conceptualising the combination of information quality evaluation, valuation approach choice and uncertainty analysis. We do not claim that this is, as yet, a well-defined model or method, but rather offer it as a way of conceptualising valuation decisions under information scarcity and asymmetry that awaits empirical validation and practical assessment. This would require a systematic literature review of valuation and decision-making research in general, to then be subject to empirical validation.

RESEARCH GAP AND OBJECTIVES

Research gap

There's one main problem with the data when we try to look at how unlisted companies are valued. This is because the data we lack is often incomplete and difficult to verify. Several papers have been published which have looked at ways to solve these problems. Vayas-Ortega et al., studied using DCF valuation and machine learning techniques for unlisted companies valuation. A number of papers have previously shown the use of simulation based models to better understand risk and uncertainty of valuation [1][2][3]. Machine learning techniques have been shown to be useful in valuation of start ups and conduct comparable analysis [4][5]. Overall it has been established that there are various techniques, but they all depend upon the amount and quality of data that is available.Another challenge is the selection of the relevant peer companies. Jagrič et al. reviewed intelligent techniques to enhance comparable company analysis with multiple applications to value private companies [6]. Geertsema and Lu studied applying machine learning algorithms to identify comparable peer companies [5]. Bourveau et al. examined the impact of accounting comparability between public and private companies on the value relevance of the financial information in private companies [15]. These examples demonstrate that having financial data, in itself, is not sufficient to be able to value a company because the information must be relevant, comparable, consistent, complete and credible.
Additional work has been carried out around information bias, uncertainty and lack of data in private markets. El-Al et al. conducted a study on the validity of valuations of companies and the bias and information levels in expert valuations versus market valuations [7]. Selvam and Whittaker presented the problem with inaccurate, noisy, incomplete and potentially biased data involved in private market deals [10]. Ernst

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examined simulation based valuations [3], Bottazzi et al. examined uncertainty in valuations with DCF [11], Blanquet et al. examined using machine learning techniques to improve the explainability of company valuations [16]. All of these papers clearly show the importance of understanding the assumptions made when valuing and knowing how the valuation has been derived then explaining the uncertainty ranges. Other authors have looked at how information affects the value of a company, and have used various methods to examine this. Mohan et al. looked at various methods to value the use of enterprise data within an organisation [8]. However this work was not directly related to the author as it was looking at valuing data as an asset. Another paper has considered information and firm value. Mohan et al. considered how to value enterprise data as a value added asset [8]. Valuing data as an asset is one step away from assessing the completeness of the data in a particular company. It does, however, demonstrate how data could be considered as a valuable asset. Abideen and Wu considered how to use investor sentiment as an alternative input for a machine learning algorithm to value companies in the Chinese stock market [9]. This indicates the possible usefulness of the alternative sources of information, but for other market (or unlisted) firms, the data (sentiment and prices) required will not exist. Reviews by El-Masri et al. and Colombo et al. give overviews of the different factors, indicators and methods that are used to value early stage companies [13][14]. However these do not suggest a specific method to assess the completeness of information.

The level of the ICS has been suggested to avoid this by providing an indication of the degree of data that is potentially valuable and credible. In terms of looking at the research differently we can see there are issues with lack of data and the uncertainties that result. A business may have complete and perfect financial data, nevertheless it can be difficult to tell how much the earning, costs, cash flows and growth of the business will be, this is called performance uncertainty. How much of the valuation uncertainty is caused by the lack of credible data? What kind of uncertainty does the lack of data cause? The valuation is based on the wrong assumption, or maybe the wrong model [3][11] of the business, this is definitely a method of valuation under such conditions, however it may not be as a result of incomplete information. These issues are valid but different and as such need to be considered separately. Simulation and stochastic valuations can be used to make sure the valuations are not affected by these uncertainties [3][11]. The research has been conducted on the issues with incomplete and incredible data on private markets [10].

The third set of data that could be used in researching valuations in India is company information and documents provided from the Ministry of Corporate Affairs. As there is a lack of data available in India [12], this may help fill the gap. Not all unlisted firms may have good, complete, up-to-date, and verifiable data, so care must be taken when judging how good the data is. Charumathi and Ramesh studied voluntary disclosure and firm value in non financial firms on the BSE 100 Index [17]. Again there is some valuable evidence here about corporate disclosure and valuations in India. Yet it is limited to listed firms, and whilst this highlights the types of key issues that must be taken into consideration when choosing sources and judging data quality, this does not explain how the completeness of the data can lead to choosing the right method of valuation.The research we have examined has already established that there is little known about how to assess the information available for individual unlisted companies. A method is required which can incorporate the completeness and quality of the information into a ranking method in order to determine the most appropriate valuation method. We have described the ISAV framework which utilises the ICS as to rank information available for a business.You can read the definitions of the ICS below: The ICS is intended to tell whether the data that is present can be used with any valuation method; the s is not intended to be used to tell the likelihood of obtaining the correct result or how close the estimate is likely to be. It can be used to tell whether the technique can be easily used with the data, whether it should be adapted or whether it is unlikely to be used because of missing data.This has been identified using the literature selected and reviewed but doesn't necessarily mean there isn't already a method currently in operation. This framework would need to be explored in much more detail to establish whether it's unique and how it compares with any other method that is similar.

Research Objectives

The overall goal of this research is to create a model that helps adjust the way unlisted companies are valued based on how complete and reliable the information's

The specific goals are:

1. To look at existing ways to value companies. Examine discounted cash flow, machine learning, similar company multiples, simulation and stochastic valuation. Find what they contribute, what assumptions they use and what limits they have for unlisted companies [1]–[7] [10] [11].

2. To find the parts of information quality that matter for valuation. Look at how complete the financial statement completeness, how recent the disclosure is, how reliable the source is, how much transaction evidence there is, how similar the peer companies are and how clear the business model is for deciding if the data supports a certain valuation method [6] [10] [12] [15].

3. To suggest the ISAV model and ICS. Build a way to check how complete the information is and use that check to choose, adjust or not use valuation methods based on the data for a company.

4. To tell apart. Explain different types of uncertainty. Separate uncertainty in business performance uncertainty in information uncertainty in how similar the peer companies uncertainty in the model. Think about how to talk about assumptions, limits, scenarios and valuation ranges [3] [7] [10] [11] [16].

5. To look at how the model works for companies in India. Think about how official company information sources and existing Indian disclosure research can help with the model while also pointing out the limits of the data and the need for more real tests [12] [17].

PROPOSED CONCEPTUAL FRAMEWORK

ISSN: 3139-0862

Overview of the Proposed Framework

This framework should enable an understanding of how the quantity and quality of information available will influence the valuation method choice of an unlisted company. Information Scarcity Adaptive Valuation (ISAV) framework aims to create a valuation process adaptive to the quality of evidence available. The framework has been developed from research relating to DCF, machine learning-based Enterprise Valuation, Comparable Company Valuation and uncertainty. Whilst DCF can be used to give a known intrinsic value estimate, it is subject to assumptions in cash flow forecasts and discount rate [1]. Machine learning-based methods can assist in illustrating the relationship of certain financial and contextual factors, however relevant data must be available [2][4][5]. Comparable company valuation hinges on being able to identify comparable companies with quality financial information [6][12]. Probabilistic or simulation approaches can be used to factor in to unmodelled uncertainty, but the output is still based on assumptions and evidence [3][13].This allows ISAV framework to shed some light on how the information quality could be integrated into the valuation process.

There are 6 steps in this framework:

1. Collect and verify evidence
2. Build information quality and financial features
3. Compute ICS (Information Completeness Score)
4. Choose appropriate valuation method(s)
5. Reconcile estimates and understand uncertainty
6. Create an explainable report.

The framework is not intended to replace traditional valuation techniques. Instead, its purpose is to suggest a structure for how to choose what techniques to use, what assumptions to draw down and when there is insufficient evidence to provide a justifiable estimate.

Figure I. Proposed conceptual workflow of the Information-Scarcity Adaptive Valuation (ISAV) framework.



Information Completeness Score

The goal of the Information Completeness Score (ICS) concept is to provide an approximate measure of evidence that exists. The first algorithm is in the shape of financial information, evidence of transactions or funding, quality of comparable company information and visibility of the business model. Breakdown of the detailed score and criteria results in 5 scoring criteria.

Table I. Proposed dimensions of the Information Completeness Score

Dimension	Weight	Purpose and assessment criteria
Financial completeness ((d_F))	0.30	How complete the financial information is (revenue, EBITDA, EBIT, Profit after tax, Free Cashflow, Assets, Liabilities, Debt, Cash).
Transaction and market evidence ((d_T))	0.25	How complete, up-to-date and relevant the disclosure of funding rounds and acquisitions are (transaction value, valuation multiples)
Peer-data quality ((d_P))	0.20	How many comparable companies there are. How 'good' the financial information is. How comparable the companies are (industry, size, country and valuation evidence).
Business-model observability ((d_B))	0.15	How visible the recurring revenue, customer concentration, employee trends and business model characteristics are.
Disclosure recency and source quality ((d_R))	0.10	How up-to-date the disclosures are. Reliance on primary sources (audited statements, MCA filings). Reliability of information sources.

The objective is to be able to produce a score of 1 for each of the dimensions. The more evidence under the criteria the higher the score. From the original design of the criteria, the overall ICS is constructed by the following:

$$ICS = 0.30d_F + 0.25d_T + 0.20d_P + 0.15d_B + 0.10d_R$$

The score weights are based on the original design of the system. Therefore the weights are not necessarily accurate. The scoring system needs to be very clear, so different people scoring a company will come to the same results.

The scoring details give scored examples for each criterion. Eg Financial completeness – is the financial complete? (How many years of financial?), Relevant Financial information? Missing or inconsistent information? Transaction – is there relevant transaction information? (Value, relevant multiples,?) Comparable quality – How many comparable are there? Similar? How similar? Business model visibility – How visible are the operating and revenue characteristics? Source quality – How recent and reliable is the information?

ISSN: 3139-0862

Adaptive Selection of Valuation Approaches

Principle: the valuation method adopted must be determined by the amount, quality and relevance of information available. Starting from the algorithm, we have 3 levels of information:

1.High information:

More granular DCF could be used since there are a sufficient number of accurate financials. Market multiples could be applied. If there is sufficient available training data machine learning estimates could be applied [1][2][5][6].

2.Medium information:

More assumption would need to be qualified. Less data driven methods could be used. If there are sufficient relevant and comparable companies then comparable or transaction data could be used. The method should be the one that can provide the relevant information needed.

3.Low information:

There would be fewer assumptions on company specifics. If they can be substantiated then scenario analysis or wider industry assumptions could be considered. Hierarchical or Bayesian approaches could be suitable if assumptions and priors are reasonable. If no sensible estimate can be made then this should be stated.

The level of ICS should specify what valuation methods are appropriate and the level of qualification that is required. The same score can be calculated from different levels of information quality which will influence the appropriate valuation methods.

Valuation Estimation and Uncertainty Analysis

Once you have selected the valuation method, you can then generate an enterprise value estimate based on the valuation methods you know your information supports. You can generate intrinsic value estimates based on DCF if you are able to support forecasts and discount rate assumptions. You can generate market based estimates based on comparable or transaction multiples if you know a suitable set of comparable transactions that you are able to validate. You can generate further estimates based on machine learning if sufficient relevant data and validation is possible.

If there is more than one estimate then compare assumptions and note any significant differences. Do not combine estimates unless they are multiple methods. The estimates may differ because of different assumptions.

There are two different types of uncertainty: Uncertainty from the business and Uncertainty from lack of information Uncertainty from the business can be from the revenue, operating costs, competition and future cash flows Uncertainty from information can be from missing financial, old information, unreliable information sources and not enough comparable transactions. Uncertainty can also be from the valuation method. Simulation and probabilistic methods can provide an estimate of the uncertainty but it will be based on the information and assumptions [3][13].

The output should be an estimate of enterprise value if it can be assumed to be reliable. If assumptions have been made then a range/scenarios should also be made available. It should also include the quality of the data, the methods used, the main assumptions made and the main limitations of the method used. The main idea of this framework is that the less trustworthy information is, the more assumptions should be held to a minimum of the company's specifics and the more the uncertainty should be communicated.

More information about the extent of the valuations should not be imposed by the ICS. Completeness of the information and uncertainty of the forecasts are two different issues. More research is needed to correlate the score with the extent of the range.

Figure II. Conceptual distinction between business uncertainty and information uncertainty in unlisted-company valuation.

Valuation Uncertainty

↓ ↓

Business Uncertainty *(Inherent to the firm)*	**Information Uncertainty** *(Caused by data limitations)*
• Future demand	• Missing / incomplete financials
• Competition	• Outdated disclosures
• Cost structure	• Weak or few comparables
• Cash-flow volatility	• Unreliable sources

Explainability and Evidence Traceability

The report should include an explanation of why you have chosen a particular valuation methodology, what evidence you have used to support important assumptions and the limitations. This is pertinent to work on valuation credibility and explainable machine learning [7][10].

Where possible, the source of the input should be recorded, together with the time horizon, and whether the input has been checked. Any gaps should be highlighted, together with any material inconsistencies and variances across valuation approaches. This will introduce transparency so that the source information can be checked and compared. This does not mean that source data is correct or that the estimate is accurate.

The suggested application in India will use company data which can be collected from corporate reference sources, or other sources [16][17]. The framework should also offer insight into the veracity of the data, whether it is validated, self reported, calculated or missing. There may be some background data from researches into self-disclosure and valuation of Indian listed companies but this should not necessarily be applied to unlisted ones [18].

Conceptual Workflow and Expected Contribution

The proposed ISAV framework involves 6 steps:

Collect and verify: What financial information, company information, industry signals, funding/transaction data and source dates are available? Verify the data is consistent, sourced from a credible source and is relevant.

Build Features and score ICS: Make financial signals. Score 5 information quality factors.

Choose valuation method: Apply your information quality to determine which valuation methods qualify, need qualifying or should not be used.

Valuation: do DCF, comparables or transaction multiples and machine learning or not if you can defend the data and assumptions.

Reconcile estimates and understand uncertainty: Compare the results, noting differences and putting them into context. If significant discrepancies are found, they should be explored. Conduct a sensitivity/ scenario analysis where feasible.

Comments: Include number of companies included in database analysis, number of countries and time period included. Explain: Give an indication of enterprise value, where appropriate. State how calculated, main assumptions, data quality warnings, sources of uncertainty and what evidence is available.

The proposed ISAV framework is conceptual and has not been validated.The key contribution from this framework is that it gives a guide to which valuation techniques to employ, given the information completeness and quality. This relates information quality back to value estimation, uncertainty and explainability of reporting. There has been published work on valuation using DCF, machine learning based valuation, selection of comparables, simulation, and uncertainty [1-6][11-13] but a structure to determine which valuation element is most suitable for a non-listed company has yet to be explored.

Additional analysis should be done on the effect of different weights and thresholds on the sensitivity of the ICS. The criteria for scoring should be tested

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to ensure it can be used reliably by independent observers. Where the data exists, the recommendations should be compared to conventional valuation practices; this should be done before the approach can be considered as a robust valuation technique.

The suggested weights, scoring rubric, cut-offs, and method-selection rules need to be tested more. The impact of using different weights and cut-offs on the ICS should be studied, and it should be verified whether independent evaluators are able to do consistent ratings with the scoring rubric. The framework's recommendations need to be tested against conventional valuation practice whenever the data permit.

FUTURE RESEARCH

A method that takes information into account might work well for Indian unlisted companies, since what they share, how they do business, and comparisons with similar companies can be very different. Some company information might be available from the corporate data and public-document services of the Ministry of Corporate Affairs, though the access, coverage, availability and completeness of this would have to be checked on a case by case basis [12]. The framework should be explicit about the fact that public filings are not necessarily the most up-to-date or complete source of information for a company's financials. Data availability and quality should be noted in the valuation.

Future research should: 1) review more studies to confirm whether the gap is really unique, 2) make clear guidelines for what counts as solid evidence and check if different reviewers use them the same way, and 3) see if the framework's tips for choosing methods work better than usual in a group of private companies that have enough data. The evaluation should control for transaction date, sector, geography, company size, and selection bias. Because private company deal values are usually not shared or only shared sometimes, the limits of the data used for evaluation need to be clearly explained.

Another research question concerns whether users would understand a valuation range, and the evidence-quality explanation accompanying that range, better than a single point estimate. This can be tested with either an expert review, or a structured experiment with a sample of users. This kind of work would assess whether the framework increases transparency and usefulness or just generates another score.

CONCLUSION

The literature shows that valuing unlisted companies poses challenges due to uncertainty around forecasting, imperfect comparable data, few private transactions, lack of transparency and potential bias in valuation. Issues such as DCF, market multiples, machine-learning, simulation and probability techniques help to overcome some of these issues, however they are reliant upon the quality and relevance of the data available. This paper provides a solution to these issues using an integrated decision support framework called ISAV.

By collecting and verifying evidence, developing financial and information quality features, selecting an appropriate valuation methodology, estimating and reconciling the valuation, quantifying the uncertainty and providing an interpretable output with data quality flags and audit trail. The initial ICS bands are not validated, they are just hypotheses. This paper is purely a conceptual piece based on literature. There is no empirical evidence of the framework working well or the valuation being accurate. Further systematic reviews and empirical tests would be required for this framework to become an established technique, particularly when applied to Indian unlisted companies.

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