Business Valuation: AI Applications and Sustainable Metrics Integration across Diverse Industries

IOSIF HRISCU, University of Twente, The Netherlands

Business valuation is essential for understanding a company's value, but traditional methods may no longer suffice in today's dynamic market. This paper explores two key areas: the role of artificial intelligence (AI) in valuation and the integration of sustainable factors in new business valuation methods. AI can enhance the precision of these methods across industries, while sustainability needs to be integrated in the business valuation methodologies. By examining current practices, this research aims to provide insights for navigating modern valuation challenges. The study's findings reveal that AI technologies significantly improve the accuracy and efficiency of business valuations. Moreover, studies have shown that environmental, social and governance (ESG) factors can positively influence both business performance and market value.

Additional Key Words and Phrases: Artificial Intelligence, Business Valuation, Customer Value, ESG factors, Machine Learning, Sustainability

1 INTRODUCTION

Business valuation is a crucial aspect of analyzing and valuing any business, regardless of its size and complexity. It serves for investors and stakeholders, providing insights into the financial health, performance and potential growth of organizations [Kwok 2008]. However, the complexities of modern markets and the appearance of new technologies and sustainability regulations regarding business' practices [OECD 2024], make traditional approaches to no longer be sufficient. Consequently, there is a pressing need to explore innovative methodologies and considerations that can enhance the accuracy of business valuation practices.

This paper explores two dimensions related to business valuation: the potential of AI technologies and the integration of sustainable features into valuation methods. With AI technologies revolutionizing data analysis and decision-making processes, there exists an opportunity to leverage these tools to enhance the precision and efficiency of business valuation across diverse industries [Dai 2022; Enholm et al. 2021; Glavas 2023; Koczar et al. 2023]. In the context of this research, when we refer to "business", we encompass a broad spectrum of organizations and enterprises regardless of their size, profitability or any other similar factors. This includes, but is not limited to, small and medium-sized enterprises (SMEs), large multinational corporations or start-ups.

TScIT 41, July 5, 2024, Enschede, The Netherlands
© 2023 University of Twente, Faculty of Electrical Engineering, Mathematics and Computer Science.
Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

Moreover, as sustainability regulations [Commission 2023] are becoming more common, there is a growing recognition of the need to incorporate ESG factors into business valuation models [Koczar et al. 2023]. By integrating sustainable features into valuation frameworks, companies can align their financial performance with broader environmental and social objectives, providing trust for stakeholders and increasing their competitive advantage [Koczar et al. 2023].

This research aims to explore the current landscape of business valuation, examining current methodologies and opportunities. By showcasing the existing methods to business valuation and highlighting their limitations, we aim to underscore the importance of embracing innovation and sustainability principles. Through a comprehensive analysis of AI applications and sustainable metrics integration, we aim to provide insights and recommendations for companies/analysts seeking to navigate the complexities of modern business valuation. In addition to its implications for industry, this research also contributes to academia by advancing our understanding of contemporary business valuation practices. The comprehensive analysis of AI applications and sustainable metrics integration, offers new perspectives that can contribute to the ongoing discourse in the field of business valuation.

1.1 Problem Statement

As businesses navigate complex market dynamics, the traditional approaches to measuring business value may fall short in capturing the nuanced factors that drive success and sustainability [Miciuła et al. 2020]. This gap underscores the need for a comprehensive understanding of how technology can enhance the process of measuring business value across diverse industries. Moreover, as sustainability emerges as a critical consideration in contemporary business practices, there is a growing demand for knowledge into the specific sustainable features and metrics that influence business valuation models.

1.2 Research questions

The problem statement leads to the following research questions:

(1) *How do AI technologies contribute to measuring business value across different industries?*

(2) *What specific (sustainable) metrics are commonly utilized in business valuation models and how do they contribute to determining business value?*

The following subquestions have been derived to help answer the main research questions:

(1) What are the prevailing methodologies and practices used in contemporary business valuation?

(2) Which specific attributes are commonly incorporated in assessing business value?

The first subquestion is used to analyze the current methodologies of business valuation and showcase the potential limitations that could be addressed through the implementation of AI technologies. The second subquestion gives an insight on the features that are being used while measuring business value and the possibility of integrating new sustainable factors.

The semi-systematic literature review approach is well-suited for exploring topics that have been conceptualized and studied differently across various disciplines [Snyder 2019]. This method allows for a comprehensive overview of a topic, examining how research within a selected field has progressed over time. By synthesizing meta-narratives rather than measuring effect sizes, the semi-systematic review identifies all potentially relevant research traditions and their implications for the studied topic. This approach is particularly useful for detecting themes, theoretical perspectives, and common issues within a specific research discipline, thereby mapping the field, synthesizing current knowledge, and setting an agenda for future research [Snyder 2019; Wong et al. 2013].

2 RESEARCH METHODOLOGY

As literature review lays the foundation for academic investigations, this section details the steps taken in order to answer the research questions [S et al. 2024]. Considering the gaps in literature regarding the two topics of AI and sustainability in the context of business valuation, the type of literature evaluation performed is semi-systematic [Snyder 2019]. Semi-structured reviews are designed to provide a broad understanding of a particular research area, allowing for flexibility in the selection and analysis of sources while still maintaining a structured approach [Wong et al. 2013]. The main phases of the research consist of: planning, execution, and reporting [Brereton et al. 2007; Kitchenham and Charters 2007].

The first phase starts by establishing the research questions and search queries. Subsequently, we develop and validate a review methodology to guide our data search and analysis. The last step of this phase constitutes of developing review protocols such as criteria for inclusion from Table 1. During the execution phase, the selection of articles implies finding in the existing literature papers that lead to the answers of the research questions. Partly, this is done by applying the criteria for inclusion on the selected papers. The papers are collected from three distinct sources to ensure a comprehensive review and the entire process is presented in Figure 1. First, using a structured literature review on Scopus[1], we identified 11 relevant papers. Considering the significant reduction in the number of papers (from 169 to 11) after applying the inclusion and exclusion criteria, it is important to note the subjectivity involved in the selection process based on title, keywords, and abstract. Our strategy involved defining three key pillars: business valuation, AI, and sustainability. These pillars were chosen as they represent the core focus areas of this research. Only papers that addressed at least two of these pillars were selected, ensuring the inclusion of the most relevant studies. Second, external tools like Semantic Scholar[2] and Elicit[3] contributed with an additional 7 papers, collected manually. Lastly, by using targeted queries on Google Scholar[4] 18 papers have been collected semi-systematically. Due to a low number of papers (36) displayed after using the two queries from Google Scholar, we decided to evaluate all of them based on title and abstract and only select the most relevant ones. Data analysis and synthesis is performed on these papers in order to find relevant information that helps answer the research questions. In the final phase, the output of this paper is presented in comprehensive reports based on the analysis of existing literature where the findings are discussed in order to highlight the main takeaways.

Scopus is chosen as the main database for the literature review due to its vast collection of scientific articles and advanced search capabilities [Kushwaha et al. 2021; Ngai et al. 2009]. The advanced search function was utilized to create custom search queries, incorporating specific keywords such as: 'Artificial Intelligence', 'Machine Learning', 'Lifetime Value', 'Business Value', 'CLV' (Customer Lifetime Value), 'LTV' (Lifetime Value), 'Metrics', and 'Features'. These keywords, in combination with logical operators 'AND' and 'OR', facilitated the crafting of one main search query:

- ("AI" OR "ML" OR "Artificial Intelligence" OR "Machine Learning") AND ("Lifetime Value" OR "Business Value" OR "Business Valuation" OR "CLV" OR "LTV") AND ("Metrics" OR "Features")

The papers that have been collected manually, are chosen from the aforementioned websites because of their ability to efficiently provide relevant papers. Semantic Scholar offers advanced search capabilities and AI-driven recommendations. Elicit leverages AI to extract and summarize key information from research papers.

Google Scholar is utilized for the collection of the semi-systematic review due to its extensive repository of academic publications and ease of access to diverse sources.

The following search queries were employed:

- allintitle: "customer lifetime value" OR "sustainability" OR "artificial intelligence" OR "machine learning"
- allintitle: "sustainability" OR "artificial intelligence" OR "machine learning" OR "business valuation"

The total number of papers collected through this methodology is 36.

[1]https://www.scopus.com/

[2]https://www.semanticscholar.org/

[3]https://elicit.com/

[4]https://scholar.google.com/

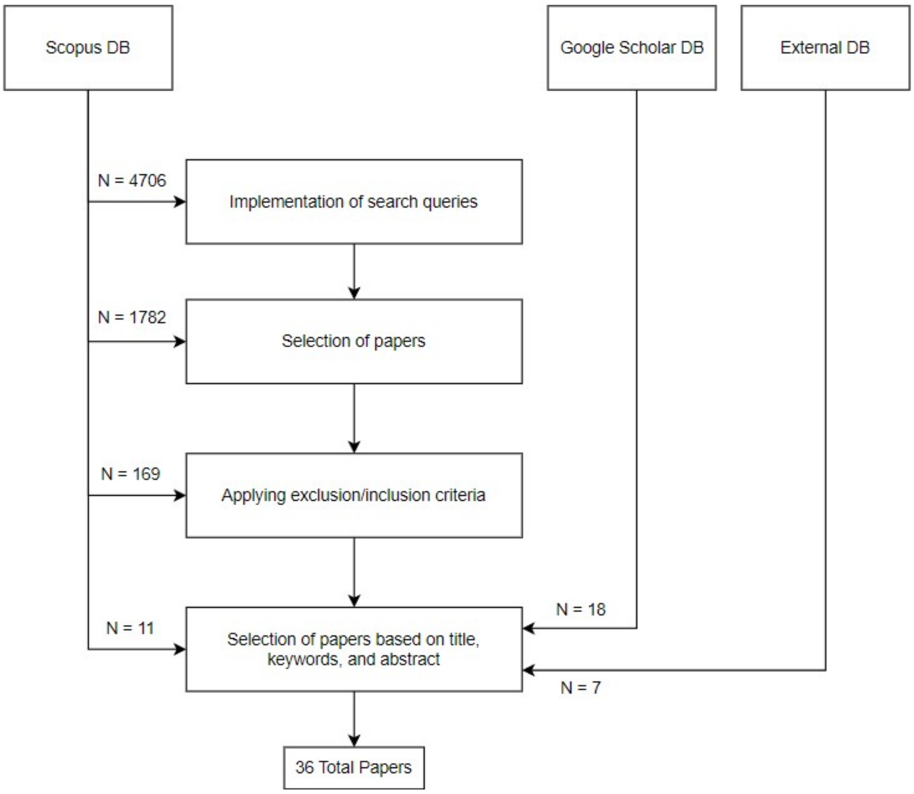

Fig. 1. Illustration of the article selection process

Table 1. Summary of article selection criteria

Criteria	Decision
Subject area of Business, Management and Accounting	Inclusion
Article written in English	Inclusion
Article from scientific journals	Inclusion
Article published before 2018	Exclusion
Duplicates of an original article	Exclusion
Relevance of abstract, title, and content to research objective	Exclusion
Unavailability of the article online for free	Exclusion

The methodology used guarantees a robust and highly relevant selection of articles for this systematic review.

3 DECONSTRUCTING THE RESEARCH LANDSCAPE

This section provides a unique lens to examine the academical work surrounding the application of AI techniques and the use of sustainable factors for business valuation.

Figure 2 represents a word cloud generated from the articles used in Table 3, excluding the words from the research questions, offers several key insights. It is important to note that the size of each word in the word cloud directly corresponds to the frequency of its appearance, the bigger the word, the more frequent it is. One important aspect is the frequent appearance of ESG factors, indicating that when sustainable factors are introduced into business valuation methods, they are likely to be ESG-related. Additionally, terms such as "data", "performance", "factors" and "analysis" emphasize the importance of data-driven approaches and performance metrics in valuation. This highlights how AI technologies facilitate the collection, analysis, and utilization of vast data sets to derive accurate valuations across diverse industries. The terms "predictive", "regression" and "random forest" indicate the use of statistical and machine learning models in business valuation, aiding in forecasting future business performance. The presence of "environmental" and "economical" suggests that both environmental sustainability and economical factors are pivotal in valuation models, aligning with the research's aim to explore sustainable metrics and their contribution to determining business value. Furthermore, words such as "customer", "company", "CLV", and "management" indicate that customer-centric metrics and company performance indicators are integral to valuation models, helping to understand how customer behavior and company management practices influence overall business value. Financial and capital aspects are also emphasized through terms like "cash", "flow", "capital" and "assets" highlighting the continued relevance of traditional financial metrics alongside newer sustainability-focused metrics. In summary, the word cloud underscores the integration of AI technologies, the significance of ESG factors, and the ongoing importance of financial and performance metrics in developing new valuation models.

The majority of the papers collected for this research are from the years 2022 to 2024, indicating that the exploration of AI, and sustainable metrics in business valuation is a relatively new and rapidly evolving field. Although papers published before 2018 were excluded, only 26 were published between 2003 and 2017. This recent surge in academic attention indicates the growing recognition of the importance of integrating advanced technologies and sustainability considerations into traditional valuation models.

Table 2 enumerates the majority of the articles, indicating the journal of publication, the number of citations, and the impact factor of each journal. Three studies stand out [Abdi et al. 2022; Alshehhi et al. 2018; Aydoğmuş et al. 2022] with high citation scores, highlighting their significance in the field. The papers [Blessing and Klaus 2023; Boeijink 2024; Dai 2022; Damodaran 2012; Glavas 2023; Iuraș et al. 2023; Koczar et al. 2023; Kumar et al. 2023, 2021; Rath 2021; Saksonova et al. 2020; Sawant 2022; Schoormann et al. 2023] have not been introduced in Table 2 due to unavailable information about the journal in which they have been published as well as their citation and impact factor numbers.

4 AI AND SUSTAINABILITY IN BUSINESS VALUATION

There is a growing concern that current valuation models may not sufficiently account for sustainability factors, despite their potential impact on future cash flows or cost of capital. This underscores the necessity for enhanced transparency and a more comprehensive perspective on value and risk. In a recent survey [PWC 2022] conducted in October 2022 by PWC, investors were asked to rank the top priorities for businesses. Business data security and privacy emerged as the third-highest priority (51%), followed by effective corporate governance at fourth place (49%), and a focus on reducing greenhouse gas emissions at fifth place (44%). Although it is clear that investors want to see businesses focusing more on ESG factors, a significant majority (87%) of surveyed investors believe that company reporting on sustainability performance often involves greenwashing. Many cases of greenwashing occur when organizations fail to recognize that they are presenting an incomplete picture of their external impact or lack the capability or information to evaluate it thoroughly. An example of a company that saw an immediate drop in its stock price after reporting greenwashing its wood procurement is Enviva (NYSE: EVA) [Surran 2022]. Investors assign less significance to company sustainability disclosures compared to other available information, suggesting a broader skepticism towards the accuracy of companies' reporting on sustainability initiatives and achievements [Amel-Zadeh and Serafeim 2017]. Three-quarters of respondents say their confidence in sustainability reporting would increase drastically if it were assured at the same level as companies' financial statements. They increasingly demand transparency regarding the economic ramifications of companies' sustainability initiatives [Eccles et al. 2014]. A majority of investors express interest in companies disclosing the financial implications of their environmental and societal actions, yet a universally accepted methodology for such disclosures remains absent. While these disclosures are valuable for investors, they also provide company leaders with enhanced insights for guiding, financing, and implementing sustainable strategies in the long run. As stakeholders become more informed, companies are increasingly focusing on leveraging potential benefits and mitigating risks associated with external impacts [Lindgreen et al. 2008]. Even if the current financial risk seems low, ignoring potential future repercussions could pose challenges when stakeholders begin to care about these impacts. Therefore, businesses are urged to assess the economic value of their external impact, anticipate future scenarios, and integrate these considerations into decision-making processes and capital planning. The initial stage in solving this problem involves establishing a universally accepted methodology for measuring the societal cost or economic value of external impact. Such a standardized approach would facilitate comparisons between companies' impacts and provide firms with a reliable framework for understanding the financial implications of their actions.

To facilitate comprehension and provide a detailed perspective, Table 3 indexes all the literature reviewed for this study, totalling 36 papers. This table offers a detailed overview of each paper, highlighting essential aspects such as the main purpose of the research, the valuation methods, the datasets or settings used, the features incorporated in the valuation methods, and the limitations of the studies. This table not only enhances the transparency of the research process but also enables readers to follow the intellectual trajectory that led to the findings of this study. For academia, this table serves as a valuable reference that synthesizes diverse research methodologies, datasets, and outcomes, thereby providing a deeper understanding of contemporary valuation techniques and their limitations. It highlights emerging trends and gaps in the literature, offering a roadmap for future research. Regarding the business valuation industry, the table provides practical insights into the applicability of various valuation methods across different sectors, emphasizing the critical role of AI and sustainability in enhancing business performance and stakeholder satisfaction.

4.1 Business Valuation

Business valuation is the process of determining the worth of a company by assessing its assets. It involves

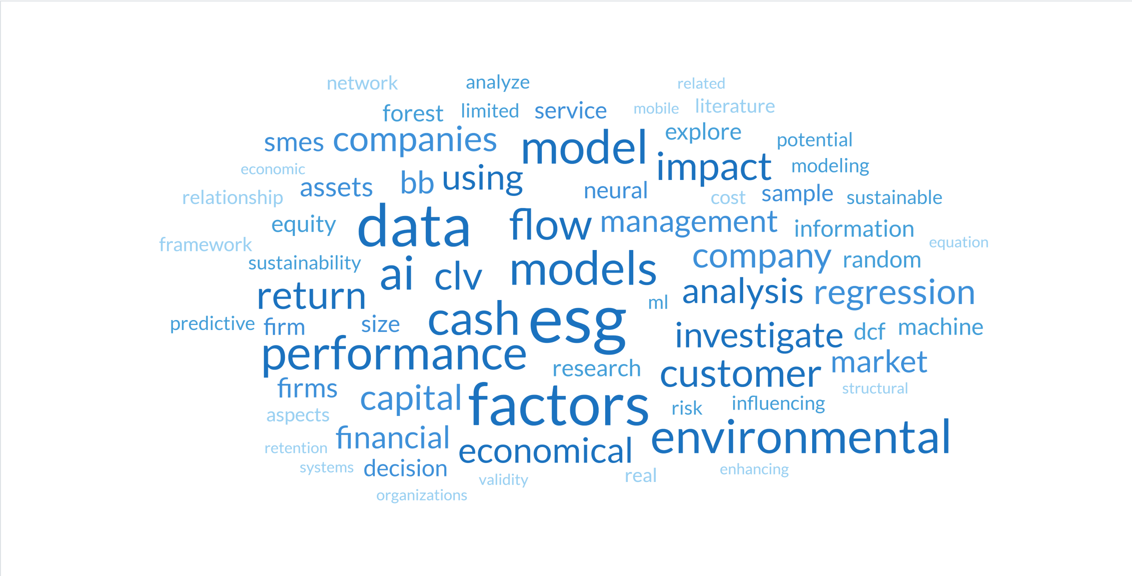

Fig. 2. Word cloud of all articles' keywords

understanding the sources of value inherent in these assets, recognizing that each asset can be valued but may require different information and methods depending on its nature [Damodaran 2012].

Valuation is based on the concept of intrinsic value, which is the present value of the expected future cash flows generated by the asset. This requires detailed financial analysis and forecasting, considering factors such as revenue growth, profit margins, and investment needs. Secondly, the choice of discount rate is crucial, as it reflects the risk associated with the expected cash flows [Damodaran 2012]. Higher risk typically demands a higher discount rate, reducing the present value of future cash flows. Market conditions and comparable company analysis play significant roles. By comparing the target company to similar firms in the industry, analysts can measure relative valuation metrics such as price-to-earnings or enterprise value-to-EBITDA (Earnings before Interest, Taxes, Depreciation, and Amortization) ratios. This comparative approach helps to ensure that the valuation is aligned with current market realities.

In business valuation, different methods for valuation are used to estimate the value of a company. These methods can broadly be classified into Traditional Statistical Methods [Dorfleitner and Gleißner 2016] and Deterministic Methods [Elena and Persida 2014]. Traditional Statistical Methods rely on historical data and statistical techniques to estimate the risk and return characteristics of investments. These methods use probabilistic models to forecast future performance based on past data (e.g. Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), Fama-French Three-Factor Model etc.) [Bottazzi et al. 2023; Ernst 2023; Kim-Duc and Nam 2024; Koczar et al. 2023; Nie et al. 2022; Rath 2021; Saksonova et al. 2020]. Deterministic Methods, on the other hand, use specific assumptions and financial projections to calculate the value of a company. These methods are straightforward and often rely on detailed cash flow forecasts and discount rates (e.g. Discounted Cash Flow (DCF), Net Present Value (NPV), Adjusted Present Value (APV), Economic Value Added (EVA) etc.) [Boeijink 2024; Glavas 2023; Iuraș et al. 2023; Miciuła et al. 2020; Wang et al. 2023]. It is important to note that obtaining a comprehensive view of a company's value is best achieved by using multiple valuation methods [Damodaran 2012; Miciuła et al. 2020]. If neither of these methods have been discussed in the papers, we categorized them into two other groups: AI Models and Literature Review. AI models leverage AI algorithms to analyze or predict company valuations. Some examples of the AI techniques encountered are neural networks [Blessing and Klaus 2023; Dai 2022; Thangeda et al. 2024], linear regression [Blessing and Klaus 2023; Dai 2022; Schoormann et al. 2023], k-means clustering [Kumar et al. 2023; Schoormann et al. 2023], random forest [Dai 2022; Sawant 2022]. Literature reviews, meanwhile, synthesize existing research on valuation methods, providing critical analysis and identifying trends, gaps, and future directions in the field [Abdi et al. 2022; Alshehhi et al. 2018; Aydoğmuş et al. 2022; Costa-Climent et al. 2023; Enholm et al. 2021; Mikalef et al. 2023; Rammer and Es-Sadki 2023; Shaik et al. 2024; Tarczyński et al. 2020; Tugui et al. 2020].

The studies from Table 3 emphasize the necessity of accurate valuation methods, such as the adjusted net assets valuation, which is remarkable for its objectivity and proximity to fair value [Miciuła et al. 2020]. The focus has shifted towards incorporating qualitative and intangible assets, especially in the context of SMEs, to reflect the true impact of sustainable practices on business value [Rath 2021]. Understanding the assumptions made while evaluating a company and carefully considering the inputs used in valuation models are crucial for accuracy [Damodaran 2012]. This is particularly important given the growing emphasis on non-financial metrics like ESG factors, which significantly influence firm valuations [Iuraș et al. 2023; Koczar et al. 2023].

4.2 Integration of AI in Business Valuation

AI encompasses systems that exhibit intelligent behavior by analyzing their surroundings and making decisions – with a certain level of autonomy – to achieve specific objectives. These AI systems can exist solely as software, operating in virtual environments (e.g., virtual assistants, image recognition software, search engines, voice and facial recognition systems). Alternatively, AI can be integrated into physical devices (e.g., advanced robots, self-driving vehicles, drones, or internet of things applications) [Commission 2018].

AI technologies significantly contribute to measuring business value across various industries. These technologies are employed to predict CLV in sectors such as e-commerce and B2B software as a service (SaaS), thereby enhancing customer retention and CRM (Customer Relationship Management) strategies [Blessing and Klaus 2023; Curiskis et al. 2023; Dai 2022; Kumar et al. 2023]. In the Banking, Financial Services, and Insurance sector, AI facilitates fraud detection, optimizing financial performance [Sawant 2022]. Moreover, AI frameworks assess the impact of climate change on firm performance and sustainability efforts in B2B markets [Shankar and Gupta 2024]. Additionally, AI supports open innovation practices and business performance by analyzing extensive data from multinational companies [Sahoo et al. 2024].

In Table 3, multiple papers highlight AI's implications in business valuation. AI's role in CLV offers enhanced resource allocation, personalized retention strategies, and it maximizes CLV [Blessing and Klaus 2023]. AI models such as Random Forest have proven effective in predicting CLV, identifying critical features like monthly premium auto, total claim amount, and coverage [Dai 2022]. Studies highlight the transformative potential of AI in enhancing business performance, particularly in B2B markets where AI frameworks for climate change competency are shown to mitigate risks and support sustainable development goals [Shankar and Gupta 2024]. The integration of AI in B2B and multinational companies fosters innovation and competitive advantage, significantly impacting business performance [Sahoo et al. 2024].

4.3 Sustainability Metrics in Business Valuation

Although the word "sustainability" lacks "solid meaning" [Lutz Newton and Freyfogle 2005], this paper focuses mainly on the three pillars, social, environment, and economic [Purvis et al. 2019] under the concept of ESG factors [Ahmad et al. 2023].

Specific sustainable features and metrics are increasingly integrated into business valuation models, providing a more comprehensive and long-term view of business value. ESG factors are essential in modern valuation models, contributing to more sustainable business assessments [Alshehhi et al. 2018; Aydoğmuş et al. 2022; Iuraș et al. 2023; Koczar et al. 2023; Segarra-Moliner and Bel-Oms 2023]. Traditional financial metrics like earnings growth, EBIT, and cash flow remain crucial, but sustainability metrics now better reflect long-term value and risks [Bottazzi et al. 2023; Ernst 2023; Kim-Duc and Nam 2024]. Furthermore, ethical aspects, regulations, and environmental pressures are critical in ensuring responsible and sustainable business growth [Enholm et al. 2021; Tugui et al. 2020]. These advancements illustrate the evolving nature of business valuation, incorporating both technological innovations and sustainability considerations to accurately determine business worth.

From Table 3, some papers mention that the integration of sustainable factors into business valuation is important. ESG factors are now seen as vital components of comprehensive valuation models, with significant implications for both short-term and long-term financial performance [Glavas 2023]. The literature underscores the positive correlation between high ESG scores and better market performance, particularly in sectors like the airline industry where firm size and age also play moderating roles [Abdi et al. 2022]. Romanian companies, for instance, are encouraged to improve their ESG reporting practices to enhance transparency and ethical standards [Iuraș et al. 2023].

4.4 The impact of Business Valuation across Different Industries

In the telecommunications industry, AI technologies have been used to improve operational efficiencies and CRM. The importance of enterprise value, EBITDA, cost of equity, and revenue diversification is significant in improving valuation through AI-driven insights [Boeijink 2024]. AI influences open innovation practices and impacts business performance in B2B organizations. A study that analyzed 398 B2B multinational companies, reveals that AI enhances innovation capabilities, leading to improved operational efficiencies and competitive advantage [Sahoo et al. 2024]. In the financial services sector, AI technologies are pivotal in improving CRM and fraud detection. AI-driven CLV models provide more accurate predictions, enabling financial institutions to tailor their services and retention strategies effectively [Kumar et al. 2023]. Additionally, the application of ML models in the banking, financial services and insurance sector for fraud detection and CLV calculation, demonstrates AI's potential in identifying fraudulent activities and optimizing customer relationships [Sawant 2022]. AI and sustainable practices also play a significant role in the valuation of start-ups and SMEs. The relationship between data network effects and business model theory highlights how AI can improve start-up valuations by identifying novel and efficient business practices [Costa-Climent et al. 2023]. Big data analytics also has an impact on stakeholder satisfaction in SMEs through the mediation of environmental and economic sustainability [Shaik et al. 2024]. In the healthcare sector, AI and sustainable features significantly impact supply chain management and risk management. AI can improve supply chain efficiency, reduce risks, and support innovation in healthcare services [Armenia et al. 2024]. The retail and e-commerce industry benefits from AI technologies through enhanced customer segmentation and predictive analytics. The integration of AI in retail helps businesses personalize marketing strategies, optimize inventory management, and improve customer satisfaction, thereby increasing their market valuation [Dai 2022]. Additionally, AI algorithms can predict and optimize CLV, further enhancing personalized marketing and targeted retention strategies in the retail sector [Blessing and Klaus 2023].

4.5 A Guideline for Integrating AI and Sustainability into Business Valuation

To enhance the effectiveness and relevance of business valuation practices, a guideline is proposed in the following lines that integrates sustainable factors with traditional valuation methods. This guideline leverages AI technologies to improve the accuracy and reliability of valuations.

The proposed guideline aims to revolutionize business valuation by integrating sustainable factors into the traditional valuation process. Through the utilization of AI technologies, the guideline enhances the accuracy and reliability of valuation models by analyzing vast datasets and identifying trends related to both financial performance and sustainability impact. By standardizing this practical guideline across all companies, regardless of size or industry, stakeholders can make more informed investment decisions that consider not only short-term financial gains but also the company's contribution to ESG objectives. A first step would be to identify key features relevant to both financial performance and sustainability impact. Then, collect multiple datasets that contain information about those key features. Develop a methodology that incorporates sustainability factors into the valuation models, quantifying their impact on business performance and long-term value creation. Furthermore, an AI model should be created that can analyze the collected data to predict future cash flows, taking into account both traditional financial metrics and sustainability factors. The AI model can be validated by using historical data and testing it against known outcomes. To assess the accuracy and reliability of the model in predicting business value, it should be tested under different scenarios. To ensure consistency and applicability of the valuation guideline across all companies, irrespective of their size or industry, the guideline should be standardized. Lastly, develop protocols for implementing the valuation method within organizations.

5 CONCLUSION

The integration of AI technologies into traditional valuation models offers a transformative approach. This advancement allows companies and analysts to better assess a business's worth by leveraging vast datasets and identifying trends related to financial performance and sustainability. The incorporation of sustainable metrics ensures that valuations reflect long-term value creation and a company's contribution to ESG objectives. For the industry, this means more informed investment decisions, improved risk management, and a stronger alignment with global sustainability goals.

In academia, this research makes a valuable contribution by expanding the understanding of contemporary business valuation practices. The analysis of AI applications and sustainable metrics integration provides new perspectives that can improve the ongoing discourse in the field. By proposing a standardized framework that integrates these advanced technologies and sustainability features, the study sets a foundation for future research in business valuation. Ultimately, this paper bridges the gap between traditional valuation methods and the emerging need for sustainability.

AI technologies significantly enhance traditional business valuation models by enabling more accurate and efficient analysis of large datasets. AI models, such as artificial neural networks and machine learning algorithms, can process vast amounts of data to uncover patterns and insights that traditional methods might miss. It has been demonstrated how AI can analyze customer retention strategies by using real-life data to predict customer value with high accuracy [Thangeda et al. 2024]. Similarly, [Dai 2022] reviewed the effectiveness of various machine learning models in analyzing CLV for e-commerce companies, highlighting key influencing factors such as education, employment status, and income. These advancements allow for more precise predictions and valuations, ultimately improving decision-making and resource allocation.

The metrics most commonly used in traditional business valuation models include revenue, net profit, cash flow, EBIT, and EBITDA [Koczar et al. 2023], which measure the financial status of a company. Integrating sustainable metrics into business valuation models ensures that valuations reflect long-term value creation and a company's commitment to ESG objectives. Studies have shown that ESG factors can significantly influence business performance and market value. For example, [Koczar et al. 2023] integrated ESG factors into business valuation methodologies to enhance decision-making and manage business value within the sustainable development framework. The relationship between ESG dimensions and CLV, finding that sustainable practices positively impact corporate financial performance [Segarra-Moliner and Bel-Oms 2023]. Additionally, the impact of ESG performance on firm value and profitability, confirming the positive relationship between ESG scores and financial outcomes such as return on assets (ROA) and Tobin's Q [Aydoğmuş et al. 2022].

5.1 Limitations and Future Recommendations

While this research provides significant insights into the integration of AI technologies and sustainable features into business valuation models, several limitations must be acknowledged. The semi-systematic literature review, although comprehensive, is limited to papers available in selected databases such as Scopus, Semantic Scholar, Elicit, and Google Scholar. Moreover, due to the recent growth in attention for these topics, the literature is limited by itself. Excluding other databases and grey literature might have led to the omission of other relevant studies. Considering the criteria applied in the selection of articles, it involved a degree of subjectivity, particularly when assessing the relevance of titles, keywords, and abstracts.

Future research should expand the scope of the literature review to include additional databases and grey literature. This would provide a more comprehensive understanding of the current state of research and practice in the field. Given the rapid pace of technological advancements in AI, continuous updates to the literature review are necessary. Researchers should focus on the latest developments and emerging trends to ensure the findings remain relevant and up-to-date. Conducting industry-specific studies would provide deeper insights into how AI technologies and sustainable features impact business valuation in different contexts. This would help in understanding the unique challenges and opportunities within specific industries. Another limitation of this research is the reliance on papers published between 2022 and 2024 (27 papers out of 36). While these recent studies provide up-to-date insights into the evolving landscape of business valuation, they may not capture the full historical context or longer-term trends in the field. This narrow time frame could result in a bias towards emerging methodologies and technologies, potentially overlooking established practices that have proven effective over time. Future research should aim to include a broader range of publications spanning multiple years to ensure a more comprehensive understanding of the subject.

In conclusion, the potential for further innovation and development in the integration of AI and sustainability into business valuation is substantial. By broadening the scope of research to include a wider range of sources and continuously updating methodologies, future studies can enhance the robustness and relevance of valuation practices. As technological advancements continue to emerge, targeted research focusing on specific industry impacts will be essential in refining these advanced valuation models, ultimately leading to more informed, sustainable, and effective financial decision-making processes.

5.2 AI Statement

During the preparation of this work the author used Semantic Scholar and Elicit in order to search for relevant literature. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

REFERENCES

Yaghoub Abdi, Xiaoni Li, and Xavier Càmara-Turull. 2022. Exploring the impact of sustainability (ESG) disclosure on firm value and financial performance (FP) in airline industry: the moderating role of size and age. *Environment, Development and Sustainability* 24, 4 (Aug 2022), 5052–5079. https://doi.org/10.1007/s10668-021-01649-w

Hadiqa Ahmad, Muhammad Yaqub, and Seung Hwan Lee. 2023. Environmental-, social-, and governance-related factors for business investment and sustainability: a scientometric review of global trends. *Environment, Development and Sustainability* 26 (Jan 2023), 2965–2987. https://doi.org/10.1007/s10668-023-02921-x

Ali Alshehhi, Haitham Nobanee, and Nilesh Khare. 2018. The Impact of Sustainability Practices on Corporate Financial Performance: Literature Trends and Future Research Potential. *Sustainability* 10, 2 (2018). https://doi.org/10.3390/su10020494

Amir Amel-Zadeh and George Serafeim. 2017. Why and How Investors Use ESG Information: Evidence from a Global Survey. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2925310

Stefano Armenia, Eduardo Franco, Francesca Iandolo, Giuliano Maielli, and Pietro Vito. 2024. Zooming in and out the landscape: Artificial intelligence and system dynamics in business and management. *Technological Forecasting and Social Change* 200 (2024). https://doi.org/10.1016/j.techfore.2023.123131

Mahmut Aydoğmuş, Güzhan Gülay, and Korkmaz Ergun. 2022. Impact of ESG performance on firm value and profitability. *Borsa Istanbul Review* 22 (2022), S119–S127. https://doi.org/10.1016/j.bir.2022.11.006

Abdullah M. Baabdullah. 2024. The precursors of AI adoption in business: Towards an efficient decision-making and functional performance. *International Journal of Information Management* 75 (2024). https://doi.org/10.1016/j.ijinfomgt.2023.102745

Elisha Blessing and Hubert Klaus. 2023. Discuss how AI algorithms predict and optimize the customer lifetime value, enabling better resource allocation and personalized retention strategies. 3329 (12 2023), 12.

Jeremy Boeijink. 2024. *Enhancing Valuation for Telcos A Strategic Approach to Business Valuation.* Master's thesis. https://essay.utwente.nl/98816/1/Boeijink_MA_BMS.pdf

Giulio Bottazzi, Francesco Cordoni, Giulia Livieri, and Stefano Marmi. 2023. Uncertainty in firm valuation and a cross-sectional misvaluation measure. *Annals of Finance* 19, 1 (Jan 2023), 63–93. https://doi.org/10.1007/s10436-022-00423-w

Pearl Brereton, Barbara A. Kitchenham, David Budgen, Mark Turner, and Mohamed Khalil. 2007. Lessons from applying the systematic literature review process within the software engineering domain. *Journal of Systems and Software* 80, 4 (Apr 2007), 571–583.

European Commission. 2018. https://digital-strategy.ec.europa.eu/en/library/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines

European Commission. 2023. Language selection | Finance. https://finance.ec.europa.eu/capital-markets-union-and-financial-markets/company-reporting-and-auditing/company-reporting/corporate-sustainability-reporting

Ricardo Costa-Climent, Darek M. Haftor, and Marcin W. Staniewski. 2023. Using machine learning to create and capture value in the business models of small and medium-sized enterprises. *International Journal of Information Management* 73 (2023). https://doi.org/10.1016/j.ijinfomgt.2023.102637

Stephan Curiskis, Xiaojing Dong, Fan Jiang, and Mark Scarr. 2023. A novel approach to predicting customer lifetime value in B2B SaaS companies. *Journal of Marketing Analytics* 11, 4 (2023), 587 – 601. https://doi.org/10.1057/s41270-023-00234-6

Xinqian Dai. 2022. Customer Lifetime Value Analysis Based on Machine Learning. *2022 the 6th International Conference on Information System and Data Mining* (May 2022). https://doi.org/10.1145/3546157.3546160

Aswath Damodaran. 2012. *Investment Valuation: Tools and Techniques for Determining the Value of Any Asset.* John Wiley Sons. https://books.google.nl/books?id=E8-30Pga-nkC&lpg=PA1&ots=9CScmptuaU&lr&pg=PA1#v=onepage&q&f=false

Gregor Dorfleitner and Werner Gleißner. 2016. Valuing Streams of Risky Cash Flows with Risk-Value Models. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2967282

Robert G. Eccles, Ioannis Ioannou, and George Serafeim. 2014. The Impact of Corporate Sustainability on Organizational Processes and Performance. *Management Science* 60, 11 (Nov 2014), 2835–2857. https://www.hbs.edu/ris/Publication%20Files/SSRN-id1964011_6791edac-7daa-4603-a220-4a0c6c7a3f7a.pdf

Miculeac Melania Elena and Cechin Crista Persida. 2014. Deterministic Methods Used In Financial Analysis. *Journal of Public Administration, Finance and Law* 3, 5 (Jun 2014), 117–125. https://doaj.org/article/4534eb20caa14089bc9bd0e38bb2cb5a

Ida Merete Enholm, Emmanouil Papagiannidis, Patrick Mikalef, and John Krogstie. 2021. Artificial Intelligence and Business Value: a Literature Review. *Information Systems Frontiers* 24, 5 (Aug 2021), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Dietmar Ernst. 2023. Risk Measures in Simulation-Based Business Valuation: Classification of Risk Measures in Risk Axiom Systems and Application in Valuation Practice. *Risks* 11, 1 (2023). https://doi.org/10.3390/risks11010013

Dejan Glavas. 2023. *Valuation and Sustainability: A Guide to Include Environmental, Social, and Governance Data in Business Valuation.* Springer Nature. https://books.google.nl/books?id=JObGEAAAQBAJ&lpg=

PR5&dq=%20%22business%20valuation%22%20%22sustainability%22&lr&pg=PP1#v=onepage&q=%22business%20valuation%22%20%22sustainability%22&f=false

Andreea Iuraș, Dorina-Nicoleta Popa, and Natalia Foltean. 2023. Business Valuation And ESG Factors – An Integrated Approach. *THE ANNALS OF THE UNIVERSITY OF ORADEA. ECONOMIC SCIENCES* 3 (07 2023), 378–390. https://doi.org/10.47535/1991AUOES32(1)028

Nguyen Kim-Duc and Pham Khanh Nam. 2024. Earnings growth rates in business valuation models: The impossible quaternity. *Global Finance Journal* 60 (May 2024), 100930. https://doi.org/10.1016/j.gfj.2024.100930

Barbara Kitchenham and Stuart M. Charters. 2007. Guidelines for performing Systematic Literature Reviews in Software Engineering | Request PDF. https://www.researchgate.net/publication/302924724_Guidelines_for_performing_Systematic_Literature_Reviews_in_Software_Engineering

Joanna Koczar, Dmitry Zakhmatov, and Venera Vagizova. 2023. Tools for considering ESG factors in business valuation. *Procedia computer science* 225 (2023), 4245–4253. https://doi.org/10.1016/j.procs.2023.10.421

Ankit Kumar, Kamred Udham Singh, Gaurav Kumar, Tanupriya Choudhury, and Ketan Kotecha. 2023. Customer Lifetime Value Prediction: Using Machine Learning to Forecast CLV and Enhance Customer Relationship Management. In *2023 7th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*. 1–7. https://doi.org/10.1109/ISMSIT58785.2023.10304958

Madhu Kumar, Debabrata Swain, Samiksha Shukla, and Lija Jacob. 2021. Prediction of Customer Lifetime Value Using Machine Learning. In *Proceedings of Second Doctoral Symposium on Computational Intelligence*, Vol. 1374. 271–278. https://doi.org/10.1007/978-981-16-3346-1_22

Amit Kumar Kushwaha, Arpan Kumar Kar, and Yogesh K. Dwivedi. 2021. Applications of big data in emerging management disciplines: A literature review using text mining. *International Journal of Information Management Data Insights* 1, 2 (Nov 2021), 100017. https://doi.org/10.1016/j.jjimei.2021.100017

Benny K.B. Kwok. 2008. *Forensic Accountancy*. LexisNexis. https://books.google.nl/books?id=Tfg8twAACAAJ

Adam Lindgreen, Valérie Swaen, and Wesley J. Johnston. 2008. Corporate Social Responsibility: An Empirical Investigation of U.S. Organizations. *Journal of Business Ethics* 85, S2 (Apr 2008), 303–323. https://doi.org/10.1007/s10551-008-9738-8

Julianne Lutz Newton and Eric T. Freyfogle. 2005. Sustainability: a Dissent. *Conservation Biology* 19, 1 (Feb 2005), 23–32. https://doi.org/10.1111/j.1523-1739.2005.538_1.x

Ireneusz Miciuła, Marta Kadłubek, and Paweł Stępień. 2020. Modern Methods of Business Valuation—Case Study and New Concepts. *Sustainability* 12, 7 (Mar 2020), 2699. https://doi.org/10.3390/su12072699

Patrick Mikalef, Najmul Islam, Vinit Parida, Harkamaljit Singh, and Najwa Altwaijry. 2023. Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. *Journal of Business Research* 164 (2023). https://doi.org/10.1016/j.jbusres.2023.113998

E.W.T. Ngai, Li Xiu, and D.C.K. Chau. 2009. Application of Data Mining Techniques in Customer Relationship management: a Literature Review and Classification. *Expert Systems with Applications* 36, 2 (Mar 2009), 2592–2602. https://doi.org/10.1016/j.eswa.2008.02.021

Dongyun Nie, Michael Scriney, Xiaoning Liang, and Mark Roantree. 2022. From data acquisition to validation: a complete workflow for predicting individual customer lifetime value. *Journal of Marketing Analytics* (2022). https://doi.org/10.1057/s41270-022-00197-0

OECD. 2024. *Global Corporate Sustainability Report 2024*. 63 pages. https://doi.org/https://doi.org/10.1787/8416b635-en

Ben Purvis, Yong Mao, and Darren Robinson. 2019. Three Pillars of sustainability: in Search of Conceptual Origins. *Sustainability Science* 14, 3 (Sep 2019), 681–695. https://doi.org/10.1007/s11625-018-0627-5

PWC. 2022. Global Investor Survey 2022 | ESG Execution Gap. https://www.pwc.com/gx/en/issues/esg/global-investor-survey-2022.html

Christian Rammer and Nordine Es-Sadki. 2023. Using big data for generating firm-level innovation indicators - a literature review. *Technological Forecasting and Social Change* 197 (2023). https://doi.org/10.1016/j.techfore.2023.122874

Paulina Rath. 2021. The impact of sustainability on SMEs and company valuation methods to measure sustainable development in SMEs Bachelor Thesis for Obtaining the Degree BSc in International Management. https://www.modul.ac.at/uploads/files/Theses/Bachelor/Undergrad_2021/BSC_2021/1821056_RATH_Paulina_Bachelor_Thesis.pdf

None Varsha P S, Amrita Chakraborty, and Arpan Kumar Kar. 2024. How to Undertake an Impactful Literature Review: Understanding Review Approaches and Guidelines for High-impact Systematic Literature Reviews. *South Asian Journal of Business and Management Cases* (2024). https://doi.org/10.1177/22779779241227654

Saumyaranjan Sahoo, Satish Kumar, Naveen Donthu, and Alok Kumar Singh. 2024. Artificial intelligence capabilities, open innovation, and business performance – Empirical insights from multinational B2B companies. *Industrial Marketing Management* 117 (2024), 28 – 41. https://doi.org/10.1016/j.indmarman.2023.12.008

Svetlana Saksonova, Neli Abramishivi, and Tatiana Papiashvili. 2020. Business valuation: classical and advanced methods. https://dspace.lu.lv/dspace/handle/7/54228

Vaibhav Subhash Sawant. 2022. Prediction of Customer Lifetime Value and Fraud Detection in BFSI using Machine Learning. https://norma.ncirl.ie/6296/

Thorsten Schoormann, Gero Strobel, Frederik Möller, Dimitri Petrik, and Patrick Zschech. 2023. Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature. *Communications of the Association for Information Systems* 52 (Jan 2023), 199–237. https://doi.org/10.17705/1cais.05209

José Ramón Segarra-Moliner and Inmaculada Bel-Oms. 2023. How Does Each ESG Dimension Predict Customer Lifetime Value by Segments? Evidence from U.S. Industrial and Technological Industries. *Sustainability* 15, 8 (2023). https://doi.org/10.3390/su15086907

Aqueeb Sohail Shaik, Asif Nazrul, Safiya Mukhtar Alshibani, Vaishali Agarwal, and Armando Papa. 2024. Environmental and economical sustainability and stakeholder satisfaction in SMEs. Critical technological success factors of big data analytics. *Technological Forecasting and Social Change* 204 (2024), 123397. https://doi.org/10.1016/j.techfore.2024.123397

Ravi Shankar and Laxmi Gupta. 2024. An integrated AI framework for managing organizational risk and climate change concerns in B2B market. *Industrial Marketing Management* 117 (2024), 173 – 187. https://doi.org/10.1016/j.indmarman.2023.12.019

Hannah Snyder. 2019. Literature Review as a Research methodology: an Overview and Guidelines. *Journal of Business Research* 104, 1 (2019), 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Carl Surran. 2022. Enviva plunges after Blue Orca short report dubs “latest ESG farce” (NYSE:EVA) | Seeking Alpha. https://seekingalpha.com/news/3890731-enviva-plunges-after-blue-orca-short-report-dubs-latest-esg-farce

Waldemar Tarczyński, Małgorzata Tarczyńska Łuniewska, and Sebastian Majewski. 2020. The value of the company and its fundamental strength. *Procedia Computer Science* 176 (2020), 2685–2694. https://doi.org/10.1016/j.procs.2020.09.331

Rahul Thangeda, Niraj Kumar, and Ritanjali Majhi. 2024. A neural network-based predictive decision model for customer retention in the telecommunication sector. *Technological Forecasting and Social Change* 202 (2024). https://doi.org/10.1016/j.techfore.2024.123250

Alexandru Tugui, Daniela Tatiana Agheorghiesei, and Laura Asandului. 2020. An Informal Ethics Auditing in Authorized Valuation for Business Sustainability in Romania. *Sustainability* 12, 20 (2020). https://doi.org/10.3390/su12208562

Jiaxuan Wang, Samira Abdullayeva, and Duc Sinh Hoang. 2023. Diversification and company sales efficiency: Synergy influence on business valuation. *Managerial and Decision Economics* 45, 2 (2023), 940–951. https://doi.org/10.1002/mde.4040 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/mde.4040

Geoff Wong, Trish Greenhalgh, Gill Westhorp, Jeanette Buckingham, and Ray Pawson. 2013. RAMESES publication standards: meta-narrative reviews. *BMC Medicine* 11, 1 (Jan 2013). https://doi.org/10.1186/1741-7015-11-20

Table 2. Journal distribution of articles

Study	Journal	Citations	Impact Factor
[Shaik et al. 2024]	Technological Forecasting and Social Change	-	3.008
[Thangeda et al. 2024]	Technological Forecasting and Social Change	-	3.008
[Baabdullah 2024]	International Journal of Information Management	-	5.266
[Armenia et al. 2024]	Technological Forecasting and Social Change	1	3.008
[Shankar and Gupta 2024]	Industrial Marketing Management	-	2.422
[Sahoo et al. 2024]	Industrial Marketing Management	5	2.422
[Rammer and Es-Sadki 2023]	Technological Forecasting and Social Change	1	3.008
[Curiskis et al. 2023]	Journal of Marketing Analytics	-	1.331
[Costa-Climent et al. 2023]	International Journal of Information Management	5	5.266
[Mikalef et al. 2023]	Journal of Business Research	16	3.238
[Nie et al. 2022]	Journal of Marketing Analytics	1	1.331
[Miciuła et al. 2020]	Sustainability (Switzerland)	10	1.198
[Kim-Duc and Nam 2024]	Global Finance Journal	-	5.2
[Tarczyński et al. 2020]	Procedia Computer Science	6	-
[Tugui et al. 2020]	Sustainability	2	3.9
[Segarra-Moliner and Bel-Oms 2023]	Sustainability	-	3.9
[Bottazzi et al. 2023]	Annals of Finance	-	1
[Ernst 2023]	Risks	1	2.2
[Wang et al. 2023]	Managerial and Decision Economics	-	1.379
[Aydoğmuş et al. 2022]	Borsa Istanbul Review	84	5.2
[Alshehhi et al. 2018]	Sustainability (Switzerland)	256	1.198
[Abdi et al. 2022]	Environment, Development and Sustainability	94	1.291

Table 3. Table reporting all the articles that have been examined to conduct the research

Study	Main Purpose	Methods for Valuation	Datasets/Settings	(Sustainable) Features	Limitations
[Shaik et al. 2024]	Examine how critical technological factors of big data analytics contribute to stakeholder satisfaction in SMEs through the mediation of environmental and economic sustainability	Literature Review	309 SMEs	Environmental and Economical	Limited sample size of SMEs
[Thangeda et al. 2024]	Analyze customer retention strategies using an artificial neural network-based decision model applied to real-life data from mobile service users in India	AI Models	311 mobile service users	Customer dissatisfaction/disloyalty/churn Adaptability, Customer service, Connectivity, Skills of employees, Advertisement, Reliability, Repurchase intention, Continuity in usage	-
[Baabdullah 2024]	Investigate the determinants influencing the intention to use AI applications among non-adopters in the Saudi Arabian context, while also evaluating and enhancing the predictive validity of the IAAAM	AI Models	-	Performance expectancy, Facilitating conditions, Personal well-being concern, Perceived threat, and Attitudes	Factors related to business organizations at the macro-level have not been covered
[Armenia et al. 2024]	Investigate the extent and direction of convergence between AI and SD within the business and management landscape	AI Models	-	Supply chain, System dynamics, Ecological and socio-economic systems, Transportation, Healthcare, Risk management, Innovation, Price control, Soft modeling	Sample restricted to Web of Science
[Shankar and Gupta 2024]	Investigate the impact of AI frameworks for climate change competency on firm performance and decision-making processes in the B2B market, with a focus on how climate change competency can mitigate associated risks and contribute to sustainable development goals	AI Models	204 service managers from B2B firms	-	Results are not universal
[Sahoo et al. 2024]	Investigate how AI influence open innovation practices and subsequently impact business performance in B2B organizations	AI Models	398 B2B multinational companies	-	Focus on multinational B2B companies
[Rammer and Es-Sadki 2023]	Address the challenges associated with obtaining indicators on firm innovation activities by exploring the potential of utilizing digital big data sources	Literature Review	Crunchbase database	-	Biased information, limited coverage, lack of accuracy and consistency, varying timeliness
[Curiskis et al. 2023]	ML framework for predicting CLV in the B2B SaaS setting, addressing challenges related to nuanced customer relationships	AI Models	-	Customer revenue stream, Product license details, Product feature usage information, and Account-level firmographic details	-
[Costa-Climent et al. 2023]	Theoretical understanding of the factors influencing value creation and capture in start-ups utilizing ML technology, by exploring the relationship between data network effects and business model theory	Literature Review	122 start-ups	Novelty, Useful, performance, Efficiency, Effort, Complementarity, Explainability, Transparency	Start-ups that may decide not to raise funds from investors do not appear in databases
[Mikalef et al. 2023]	Investigate the impact of AI competencies on B2B marketing capabilities and organizational performance	Literature Review	155 survey responses from European companies	Marketing information management/planning/implementation	Choice of method only allows us to infer causality and assume that there is a significant effect

Table 3. Table reporting all the articles that have been examined to conduct the research

Study	Main Purpose	Methods for Valuation	Datasets/Settings	(Sustainable) Features	Limitations
[Nie et al. 2022]	Develop a comprehensive framework for CLV estimation using real insurance policy data, covering all aspects from data preparation to validation	Traditional Statistical Methods	-	Retention and Acquisition rates, Future cash flow	Used only five models
[Damodaran 2012]	Explore the valuation of various financial assets and real assets, highlighting the common principles and differences among valuation models	Deterministic Methods	-	Traditional financial metrics	The book assumes relatively efficient markets, which may not always be the case in practice
[Miciuła et al. 2020]	The significance of enterprise valuation in contemporary business transactions, presenting a comprehensive overview of valuation methods and proposing the MDI-R concept to enhance valuation accuracy and fairness	Deterministic Methods	-	Assets, Income, Intellectual Capital-Market	-
[Kim-Duc and Nam 2024]	Develop formulae for earnings growth rates in business valuation models, addressing errors introduced by cross-referencing between the reinvestment rate and return on invested capital	Traditional Statistical Methods	-	Earnings growth rates, Reinvestment rate, Returns on invested capital, Future cash flows, Discount rate	-
[Koczar et al. 2023]	Integration of ESG factors into business valuation methodologies to inform decision-making and enhance the management of business value within the framework of sustainable development	Traditional Statistical Methods	-	ESG factors	-
[Tarczyński et al. 2020]	Examine the relationship between the value of the company, its fundamental strength and rates of return	Literature Review	-	Book value, Liquidation value, Replacement value, Fundamental value, Intrinsic value, Market value	Extreme level of variables may disrupt the value of the company and its fundamental power (strength) association
[Enholm et al. 2021]	Conduct a systematic literature review to understand how organizations can effectively utilize AI technologies to generate business value, while identifying key enablers, inhibitors, typologies, and effects of AI adoption and use	Literature Review	-	Ethical and Moral Aspects, Regulations, Environmental Pressure	-
[Schoormann et al. 2023]	Explore how Information Systems research utilizes AI to promote sustainable development, aiming to provide insights for informed investments and identify potential areas for future research	AI Models	95 articles	ESG factors	Neglected other perspectives (CS, environmental science), only focused on IS, neglected other research results such as purely conceptual finding
[Saksonova et al. 2020]	Comparing classical and advanced methodologies for business valuation	Traditional Statistical Methods	-	Adjusted book profit, Operating cash flow, Capital expenditures	-
[Rath 2021]	Explore the integration of sustainability into company valuation methods for SMEs, emphasizing the importance of including qualitative aspects and intangible assets to accurately reflect the impact of sustainable practices on business value	Traditional Statistical Methods	10 semi-structured interviews	ESG factors	Size of the sample is narrow

Table 3. Table reporting all the articles that have been examined to conduct the research

Study	Main Purpose	Methods for Valuation	Datasets/Settings	(Sustainable) Features	Limitations
[Sawant 2022]	Address two major issues in the BFSI sector—fraud detection and CLV calculation—by applying ML models to publicly available data from the banking and insurance domains	AI Models	Kaggle (customers in the domain of banking and insurance that contains the data related to the demographic, financial)	-	Very few numbers of research are found
[Dai 2022]	Review the effectiveness of various machine learning models—Linear Regression, Support Vector Machine, Random Forest, and Neural Network—in analyzing CLV for e-commerce companies, identifying key influencing factors	AI Models	8099 samples	Education, employment status, gender, income, location code, marital status	More datasets of CLV that can be analyze together
[Kumar et al. 2021]	Review the literature on CLV models and evaluate their effectiveness in assessing customer relationships, with the system's performance measured using a mean absolute error of 1.23%	AI Models	-	Recency, Frequency, and Monetary worth	-
[Kumar et al. 2023]	Explore how machine learning can enhance the prediction of CLV to improve CRM strategies	AI Models	Dataset of customer transactions and behaviors	-	-
[Tugui et al. 2020]	Investigate the ethical perspectives and challenges faced by authorized valuers in Romania, particularly focusing on external pressures and the role of personal reputation and social responsibility in ethical decision-making, through a nationwide survey of 558 respondents	Literature Review	Survey of 558 respondents	Ethics evaluation, Evaluation criteria, Advantages, Specific aspects, Recommendations, Gender, Age, Tenure	It captures only the general aspects of the professional's position with reference to the importance of ethics in the activity of an authorized valuer
[Glavas 2023]	Provide readers with methods to value businesses using financial models that factor in ESG data	Deterministic Methods	-	ESG factors	There is no universal agreement on the techniques for integrating ESG data into valuation multiples.
[Blessing and Klaus 2023]	Explore how AI algorithms can predict and optimize CLV by analyzing vast customer data and employing machine learning models, thereby enhancing personalized marketing, targeted retention strategies, and efficient resource allocation for businesses	AI Models	-	Purchase frequency, Average order, Value	AI algorithms aren't infallible
[Segarra-Moliner and Bel-Oms 2023]	Analyze the relationship between ESG dimensions of corporate sustainability initiatives and CLV across different segments of U.S. listed firms, using prediction-oriented modeling to test hypotheses and evaluate the predictive validity of a partial least squares model	AI Models	547 U.S. listed firms from the Refinitiv Thomson Reuters Eikon database	ESG factors, Corporate financial performance, Fuzzy set qualitative comparative analysis, ROA, Tobin's Q, Stock market return	Dataset with firms only from US and it considers profit margins as free cash flow and net sales
[Bottazzi et al. 2023]	A robust methodology for company market valuation that replaces traditional point estimates with a probability distribution of fair values, enhancing the accuracy and predictive power of company valuations and market factors through econometric modeling and historical data analysis	Traditional Statistical Methods	-	Company Revenues, Balance Sheet Relations, Mispricing Indicator	The study is primarily based on publicly traded U.S. companies, which may limit the generalizability of the findings to other markets or private firms.

Table 3. Table reporting all the articles that have been examined to conduct the research

Study	Main Purpose	Methods for Valuation	Datasets/Settings	(Sustainable) Features	Limitations
[Boeijink 2024]	Investigate the strategic and operational factors influencing the valuation of telecommunications companies, particularly focusing on mobile network operators and internet service providers, and to provide recommendations for improving their valuation through qualitative analysis and expert insights	Deterministic Methods	-	Enterprise value, EBITDA, Cost of equity, Cost of debt, Revenue diversification, Cost management, Capital structure, Risk management, Investment planning, and Dividend policies	Done only in the Netherlands
[Ernst 2023]	Identify the appropriate understanding and implementation of risk measures in simulation-based business valuations, ensuring methodologically correct risk assessment to avoid valuation errorsh	Traditional Statistical Methods	-	EBIT, Cash flow	Data availability is the main barrier
[Wang et al. 2023]	Demonstrate the significance of the synergistic effect in mergers and acquisitions by analyzing various organizational indicators and using practical examples to highlight its impact on diversification and sales growth	Deterministic Methods	-	WACC, EBITDA, Income tax, Equity capital, Debt capital, EBIT, D&A, Taxes, Capital expenditures, Net working capital, Free cash flow	-
[Iuraș et al. 2023]	Potential correlations between ESG factors and business valuation by reviewing key literature and conducting an empirical analysis of Romanian companies from 2020 to 2022, highlighting the impact of ESG scores on profitability and market performance	Deterministic Methods	-	ESG factors, Operating revenues, Operating costs, Capital expenditures, Taxes	-
[Aydoğmuș et al. 2022]	Investigate the impact of ESG performance on firm value and profitability, using a large dataset to determine the relationships between overall ESG scores and individual ESG components with financial outcomes	Literature Review	1720 companies from 2013 to 2021	ESG factors, ROA, Tobin's Q	Limited sample size of SMEs
[Alshehhi et al. 2018]	Analyze the literature on the impact of corporate sustainability on financial performance, identifying trends and issues that prevent a conclusive consensus on the relationship	Literature Review	132 papers from top-tier journals are shortlisted	Economic, Environmental, Social, ROA, Return on equity, Return on investment, Earning per share, Tobin's Q, Price to earning Ratio, Market valuation, Cash flow	Limited sample size of SMEs
[Abdi et al. 2022]	Explore the impact of ESG scores on the value and financial performance of firms in the airline industry, while also examining the moderating roles of firm size and age	Literature Review	38 airlines worldwide for the period 2009 to 2019	ESG factors	Bias is too high