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Business Analytics and Digitalization as Drivers of Startup Evaluation: The Experience of the Baltic States

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Purpose: This study is motivated by the importance of startups in economic growth and the need for methods to evaluate their success, considering risk and uncertainty. The objective is to analyze factors that influence startups, using factor and cluster analysis. The hypothesis that advanced business analytics in startup evaluation can enhance the quality of investment decision-making was tested.
Methods: The combination of quantitative and qualitative techniques was used. Statistics about 20 startups from Latvia, Lithuania, and Estonia over five years were processed to identify success drivers and to group startups by similarity. Machine learning and social media sentiment analysis were applied to assess non-financial indicators.
Results: The results showed that indicators such as projected profitability, social media activity, and innovativeness are significant for startup ranking. The share of traditional methods in the Baltic states was 55%, while modern tools were 45%, highlighting the role of digitalization in risk assessment. Startups with high clustering coefficients and positive mention sentiment demonstrated superior performance.
Conclusions: The study demonstrated that integrating business analytics and digitalization enhances startup evaluation. The model combines financial metrics with network and sentiment analysis, offering a comprehensive framework for investors. It confirms that data-driven methods improve decision-making, reducing investment risks.

Keywords: *Startup evaluation, Business analytics, Digitalization, Baltic States, Economic potential, Social engagement*

1 Introduction

The current conditions of high uncertainty and dynamism in the business environment require effective decision-making approaches from investors and organizations, especially in the field of startup financing.

Startups play a key role in the innovative development of the economy, creating new jobs, developing technolo-

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gies, and contributing to market competitiveness. Startups play a key role in the innovative development of the economy, creating new jobs, developing technologies, and contributing to market competitiveness (Startup Genome, 2025).

However, investing in startups is associated with high risks due to their limited operating history, uncertainty of market success, and insufficient information about future development. Startup financing decisions require a comprehensive approach that considers both risks and opportunities.

Traditional analysis methods are often insufficient for assessing startup potential, which increases interest in using data-driven analytical tools. Business analytics methods, including descriptive, diagnostic, predictive, and prescriptive analytics, offer new opportunities for evaluating startups and making more informed decisions.

This article is dedicated to studying approaches to balancing risk and opportunity in startup investing. Particular attention is paid to the application of modern business analytics methods, including machine learning, network science, and social media analysis.

The aim of the research is to develop and evaluate analytical tools that will help investors make more accurate and objective startup financing decisions, contributing to their success and growth.

This work contributes to the development of theoretical and practical knowledge about the application of business analytics in investment activities, offering new perspectives for supporting innovation and sustainable development.

However, previous studies have mostly focused on individual aspects of startup evaluation, such as access to finance (Fisch, 2018), innovation performance (Kim et al., 2024), or the application of business analytics in SMEs (Anuradha and Sailaxmi, 2024).

Only limited research has addressed the integration of advanced analytical tools — machine learning, network analysis, and social media diagnostics — for comprehensive startup evaluation.

The research gap addressed in this study lies in the absence of a unified framework that combines traditional financial metrics with digital indicators (e.g., social media activity, network centrality) for startup evaluation.

Moreover, regional studies on the Baltic States remain scarce, despite the region's growing importance as a hub for innovative startups (Startup Genome, 2025; LSM, 2025).

Our work bridges this gap by developing and testing a hybrid multifactor model that integrates economic, technological, and social indicators, thus contributing both to academic literature and to practical investment decision-making in the context of the Baltic startup ecosystem.

2 Literature overview

2.1 Financing and survival of startups and SMEs

An analysis of available financing sources for startups and small and medium-sized enterprises (SMEs), as well as a study of the factors determining their survival and success, has shown that the sustainable development and financial stability of these organizations play a key role in economic growth, innovation, and job creation.

Traditional sources of financing include bank loans, which remain the primary financial instrument for many SMEs. However, research by Calabrese and Osmetti (2013) emphasizes the high risks of default, especially in the case of rare but significant events. The use of a generalized extreme value regression model allows for a detailed analysis of the probabilities of such risks. The study by Coleman et al. (2016) examines US startups' decisions regarding debt financing. This research helps identify financing structures and their impact on startup financial stability, providing empirical data on the factors influencing the successful use of debt.

Alternative financing sources, such as crowdfunding and venture capital, are becoming increasingly popular (Agrawal et al., 2014). Tomczak and Brem (2013) conceptualize the crowdfunding investment model, focusing on its role in diversifying startup financing sources. Teker et al. (2016) analyze venture capital markets, providing a cross-country analysis of venture capital availability for startups. The importance of non-financial information for credit risk assessment is highlighted in the work of Wahlstrøm et al. (2024). The integration of such data improves financing decision-making processes, especially in the context of SMEs (Gazzola et al., 2022).

Alternative financing for SMEs in the Baltic states, according to Rupeika-Apoga (2014), represents a significant source of financial resources.

The study by Fisch (2018) focuses on the differences in access to alternative financing sources across different regions. Factors influencing the longevity and success of startups are detailed in research by Keogh and Johnson (2021). Econometric analysis allows for the identification of such aspects as financing structure, access to capital markets, level of competition, and the adaptability of business models (Foreman-Peck et al., 2006).

Thus, the diversity of financing sources and an understanding of the survival factors of startups and SMEs require a comprehensive approach. This will allow for effective assessment of their financial stability and the development of strategies aimed at long-term success and growth.

2.2 Innovation and SME growth

Innovations have a significant impact on the growth and development of small and medium-sized enterprises (SMEs), with an emphasis on financial constraints, regional characteristics, and cooperative research and development (R&D). Financial constraints are a key barrier to SME innovation activity (Chatterji et al., 2018). Acebo et al. (2020) note that innovation subsidies can partially compensate for these constraints, stimulating investment in R&D.

However, the effect of subsidies varies depending on the level of financial accessibility: for firms with limited access to capital, such subsidies have a more significant impact (Ciampi and Gordini, 2012). This underscores the need for government support for innovation, especially in the context of tight financial constraints.

The regional context plays an important role in the development of innovation activity in medium-sized businesses. Research by Berlemann and Jahn (2015) emphasizes that medium-sized firms in regions with high levels of infrastructure and access to scientific resources demonstrate higher innovation efficiency. This is explained by the presence of local ecosystems that facilitate knowledge sharing and technological breakthroughs. Thus, territorial characteristics should be taken into account when developing SME support strategies.

Cooperative R&D is a powerful tool for increasing SME innovation activity. Research by Kim et al. (2024) demonstrates that collaboration between firms, universities, and research institutions contributes to accelerating the development of new technologies and products. The example of South Korean SMEs in the manufacturing sector shows that participation in cooperative R&D not only increases the competitiveness of companies but also reduces the risks associated with innovation activities.

Entrepreneurial activity and innovation are key factors for economic growth. Wong et al. (2005), in their research based on Global Entrepreneurship Monitor (GEM) data, emphasize that a high level of innovation in the entrepreneurial environment leads to accelerated economic development. At the same time, SMEs play an important role, contributing to job creation and technology development.

2.3 Business analytics and digitalization for SMEs

Business analytics and digitalization play a crucial role in the transformation of small and medium-sized enterprises (SMEs), contributing to increased competitiveness, efficiency, and adaptability (Melegati et al., 2019). Business analytics tools, such as Growth hacking, provide a targeted approach to business process optimization (O'Neill and Brabazon, 2019).

Research by Anuradha and Sailaxmi (2024) demonstrates how the use of such tools helps SMEs achieve growth by analyzing consumer behavior, increasing the profitability of marketing campaigns, and improving data management. Al-Debei (2023) emphasizes the importance of clearly distinguishing between the concepts of business analytics and data science. Recent research also highlights the global role of AI and digital technologies in shaping IT startup ecosystems (Hemanth and Lakshminarayana, 2025) and in promoting sustainable innovation in green startups (Fichter et al., 2025). Business analytics focuses on the practical application of data to improve decisions, while data science includes the development of complex models and algorithms. This distinction allows SMEs to effectively choose appropriate methods for their goals. Baijens et al. (2021) propose a theoretical model for data analytics management based on the VSM (Viable System Model). This model helps SMEs effectively structure data processing, ensuring flexibility and resilience to change.

Research by Ioakeimidou et al. (2024) presents a new measurement scale for assessing data analytics maturity. This tool allows SMEs to determine their current level of analytics development and formulate strategic plans to achieve a higher level of digital maturity.

AI-driven tools for startup evaluation are increasingly discussed in the context of data analytics and investment decision-making (Lutfiani et al., 2025). Kato et al. (2023) explore how the selection of relevant information affects the effectiveness of analytics. Using redundant information can reduce the quality of decisions, so it is important to identify key data for evaluating sales and testing concepts.

This trend is consistent with global findings on the evolution of IT startup ecosystems under the influence of AI (Hemanth and Lakshminarayana, 2025). Research by Qin et al. (2022) analyzes the demand for business analytics skills in various industries. This allows SMEs to adapt their analytical strategies, focusing on labor market needs and developing employee competencies in the most in-demand areas. Quansah (2024) emphasizes that the implementation of digital technologies is often associated with barriers, especially in low-income countries.

Nevertheless, digitalization is becoming a necessary element for improving operations, expanding markets, and increasing competitiveness. Yaakobi et al. (2019) demonstrate how machine learning methods can be used to evaluate and optimize organizational projects. Machine learning methods, including random forest and gradient boosting algorithms, allow for the analysis of a wide range of factors affecting performance (Blanquet et al., 2025). This is especially relevant for SMEs, which need to improve the efficiency of their operations and reduce management costs.

2.4 Regional aspect and internationalization of SMEs

The development of small and medium-sized enterprises (SMEs) is determined by both regional factors and their ability to access international markets. Regional networks, capital structure, financial institutions, and internationalization all influence SME growth and sustainability (Kaya and Persson, 2019).

Research by McAdam et al. (2015) emphasizes the importance of horizontal regional networks in the agri-food sector. Such networks stimulate knowledge sharing, collaboration, and innovation among SMEs. This is particularly important in sectors where business success depends on joint actions, such as market access, production innovation, and supply chain resilience. Regional financial institutions play a crucial role in providing capital to SMEs. Palacín-Sánchez and Di Pietro (2015) demonstrate that capital availability through regional banks and credit institutions influences SME capital structure. In regions with a developed financial sector, companies are more likely to use long-term investment strategies, while in less developed regions, short-term loans prevail. SME development depends on local policies, including the provision of subsidies, tax breaks, and support programs.

Regional governments play a key role in creating conditions for sustainable growth and enhancing SME competitiveness. The work of Wright et al. (2007) emphasizes that internationalization allows SMEs to access new markets, diversify revenues, and increase their competitiveness. International entrepreneurship promotes innovation, technology transfer, and the development of business relationships.

The main barriers to SME entry into international markets include limited financial resources, a lack of knowledge about target markets, and weak infrastructure. These barriers are particularly significant for companies operating in regions with low levels of economic activity. Internationalization also depends on the ability of SMEs to adapt to different political and cultural contexts. This requires the development of flexible strategies and the use of local partners to minimize risks. Research by Sutherland et al. (2019) indicates that employers and regional partnerships play a key role in supporting SME internationalization through training, practical assistance, and “try before you buy” programs. This approach reduces the risks associated with entering new markets and promotes gradual integration into the global economy.

2.5 Incubators, networks, and university-business interactions

The support infrastructure for small and medium-sized enterprises (SMEs), including business incubators, regional networks, and university-business interaction, plays a crucial role in the development of innovative entrepreneurship, knowledge transfer, and personnel training.

According to Aernoudt (2004), business incubators provide startups with infrastructure, mentorship, and access to funding. They help new businesses overcome barriers in the initial stages, creating favorable conditions for their growth and sustainability. Incubators act as catalysts for innovation, promoting accelerated business development through access to resources and supporting ecosystems.

Key success factors for incubators include the availability of quality mentorship, active involvement of partners from business and academia, and ensuring the accessibility of financial instruments. Incubators also contribute to the development of entrepreneurial skills, which increases SME competitiveness in the market. Research by McAdam et al. (2015) emphasizes the importance of horizontal regional networks for stimulating innovation in the agri-food sector. Such networks create a platform for the exchange of experience and knowledge among participants, contributing to the development of the local economy and enhancing SME competitiveness.

Successful regional networks are characterized by a high degree of involvement of all stakeholders, including business, universities, and government organizations. They play a key role in addressing specific regional challenges, such as access to resources and the adaptation of innovative solutions. Dada et al. (2015) explore the franchising of university-business interaction as an effective tool for knowledge and technology transfer.

Universities can contribute to SME development through training programs, research projects, and internships. This interaction is particularly important for training qualified personnel who meet business needs.

The impact of human capital on SME development is emphasized in the work of Sutherland et al. (2019). International student mobility provides a unique experience that can be used for the development of local enterprises. Students with international experience bring new knowledge and approaches, which contribute to innovation and the strengthening of ties between universities and businesses.

2.6 Entrepreneurship in times of crisis and special groups of entrepreneurs

In times of crisis, entrepreneurship plays an important role as a mechanism for adaptation and economic recovery. Support for entrepreneurship among specific groups, such as refugees, who face unique challenges and opportunities, becomes particularly important.

Research by Bizri (2017) focuses on the role of social capital in refugee entrepreneurship. Social networks, ties with diasporas, and community support are important factors helping refugees overcome barriers such as a lack of financial resources, language difficulties, and a lack of knowledge about local markets.

Social capital not only stimulates business start-ups but also creates conditions for their sustainability and growth. The work of Kolodiziev et al. (2024) analyzes the contribution of refugee-founded startups to the economies of host countries. Such startups contribute to job creation, expansion of local markets, and stimulate the development of new business models. The authors emphasize that the successful integration of refugee entrepreneurs is possible with access to funding, training programs, and support from local authorities.

Refugees face a number of unique barriers: lack of access to finance, linguistic and cultural differences, as well as restrictions in market access. These problems require targeted policies and support programs, including integration into the entrepreneurial ecosystem of host countries. Economic and social crises often become catalysts for the emergence of new business ideas. In such conditions, entrepreneurs are forced to adapt, develop innovative products and services that meet changing market needs.

During crises, SMEs play a key role in maintaining economic activity and creating jobs. Such enterprises possess the flexibility to adapt quickly to changes and are able to effectively use local resources to meet demand. To support entrepreneurship in times of crisis, it is necessary to implement financial assistance programs, tax breaks, and educational initiatives. Such measures stimulate the creation of new enterprises and strengthen their sustainability in the long term.

2.7 Forecasting and Evaluation of SME Performance

Forecasting the financial condition and assessing the performance (e.g., profitability, growth, operational efficiency) of small and medium-sized enterprises (SMEs) are key elements of their sustainable development. Research by Ciampi and Gordini (2012) demonstrates how artificial neural networks can be applied to forecast the probability of default for small businesses.

These methods allow for the analysis of complex non-linear relationships between financial indicators and risk factors, making them a more accurate tool compared to traditional statistical models.

The example of Italian small businesses shows that such approaches improve the predictive accuracy and help identify vulnerable enterprises at early stages. Jabeur and Fahmi (2017) conduct a comparative study of various financial distress forecasting models for French firms. The authors identify logistic regression as one of the most efficient methods due to its simplicity and interpretability.

However, it is emphasized that modern tools, such as neural networks and decision trees, demonstrate better performance on complex data. The article by Lu (2019) analyzes the use of Bayesian estimation to improve the predictive performance of logistic regression. This approach allows for considering the variability of predictors, which is especially important for forecasting SME financial stability.

Bayesian methods make models more adaptable to changes in data, which increases their practical applicability. Yaakobi et al. (2019) consider the application of machine learning methods for evaluating organizational performance. These methods, including random forest and gradient boosting algorithms, allow for the analysis of a wide range of factors affecting business outcomes.

Machine learning can also be used to identify hidden patterns in data, which helps improve operational processes and strategic planning. The assessment of KPIs, such as profitability, liquidity, and operational efficiency, is an integral part of SME management. Modern analytical tools integrate machine learning and statistical models to provide more accurate and timely data for management decision-making.

2.8 Research hypothesis and proof tasks

The literature review in Sections 2.1–2.7 reveals two critical gaps in startup evaluation methodologies, mentioned below.

Overreliance on traditional financial metrics (Calabrese and Osmetti, 2013; Sivicka, 2018) often fails to capture non-financial drivers of success (e.g., social media engagement, network centrality).

Limited integration of advanced analytics (e.g., machine learning, sentiment analysis) into holistic frameworks, despite their proven accuracy in risk assessment (Ciampi and Gordini, 2012; Yaakobi et al., 2019).

Recent studies (Hemanth and Lakshminarayana, 2025; Lutfiani et al., 2025) underscore the promise of hybrid models, yet they lack empirical validation in alternative contexts—such as the Baltic states. This study bridges the gap by proposing a unified approach that combines financial, technological, and social indicators, addressing the need for data-driven decision-making noted by Fisch (2018) and Rupeika-Apoga (2014).

Research Hypothesis H1:

"A comprehensive approach to risk and opportunity analysis using business analytics methods, such as machine learning, network analysis, and social media diagnostics, contributes to improving the quality of investment decisions in startups, increasing their chances of sustainable development and market success."

Research Objectives:

- Analysis of current approaches to startup risk

assessment. To achieve this objective, it will be necessary to conduct a review of traditional and modern methods of risk and opportunity analysis in startup investing; identify the limitations of traditional approaches and the need for the implementation of analytical tools.
- Development of an analytical model for startup evaluation. To achieve this objective, it will be necessary to create a model that integrates machine learning, network analysis, and social media analysis methods to assess the prospects of startups; to test the effectiveness of the model on real data.
- Evaluation of the impact of implementing analytical methods on the quality of investment decisions. To achieve this objective, it will be necessary to conduct a comparative analysis of investment decisions made using the proposed model and decisions based on traditional approaches, to assess the impact of the model on startup success indicators such as survival, profitability, and growth.
- Identification of factors influencing startup success. To achieve this objective, it will be necessary to use the proposed model to identify key factors determining startup sustainability and market success, and to compare the results with previously identified factors in the literature.
- Development of recommendations for investors. To achieve this objective, it will be necessary to formulate recommendations on the use of analytical tools to minimize risks and maximize opportunities in startup investing; to propose practical measures to improve the investment process.

Expected Results:

It is assumed that the use of modern analytical tools will improve the accuracy of assessing startup risks and opportunities, reduce the likelihood of erroneous investment decisions, and contribute to the development of a more sustainable investment ecosystem that supports innovation and economic growth.

These objectives are aimed at proving the hypothesis about the importance of integrating analytical methods into the startup financing decision-making process, which has practical and theoretical significance for the development of investment activities.

Data collection and the research itself were conducted from 2022 to 2024 in the Baltic states: Latvia, Lithuania, and Estonia.

3 Materials and Methods

3.1 Analysis of current approaches to startup risk assessment

In the Baltic states, startups play a key role in economic development, acting as engines of innovation and job creation. However, their financing is associated with high risks due to limited operating history, high market volatility, and a lack of information about future prospects. The conservative approach to risk management in Latvia may be related to limited digitalization and a habit of using time-tested methods (LSM, 2025; Stats and Market Insights, 2025a; 2025b). An analysis of the advantages and disadvantages of traditional methods is presented in Table 1.

Table 1 reveals that financial analysis is based on the analysis of balance sheet indicators such as profitability, liquidity, and debt ratio. Its advantages lie in the ease of application and the possibility of using historical data; its disadvantages lie in the limited applicability to startups due to the lack of extensive financial history. Expert assessments allow for risk evaluation based on expert opinions. Their advantages lie in the intuitive nature of the approach; the disadvantages lie in subjectivity and dependence on expert qualifications. SWOT analysis is used to identify the strengths and weaknesses of startups, and opportunities and threats. Its limitations lie in the subjectivity of quantitative assessment. An analysis of modern risk assessment methods is presented in Table 2.

Table 1: Advantages and disadvantages of startup risk assessment methods

Method	Advantages	Disadvantages
Financial analysis	Based on objective data (financial statements), it allows for assessing financial stability and profitability.	Limited availability of financial information for startups does not take into account non-financial factors.
Expert assessments	Takes into account the experience and knowledge of experts in the industry, allowing you to assess qualitative factors.	Subjectivity, difficulty of scaling, and dependence on the qualifications of experts.
SWOT analysis	Allows a comprehensive assessment of strengths and weaknesses, opportunities and threats, and takes into account the strategic context.	Subjectivity of assessments, difficulty of quantitative assessment of factors.

Source: (Sivicka, 2018)

Table 2: Comparison of modern startup risk assessment methods

Method	Application area	Advantages	Disadvantages
Machine Learning (ML)	Forecasting, classification, clustering, big data analysis, and identifying patterns.	High forecast accuracy with sufficient data, ability to self-learn and adapt to new data, and automation of processing large volumes of information.	Requires large volumes of high-quality data for training, difficulty interpreting results ("black box"), susceptibility to overfitting, and requires qualified specialists.
Social Media Analytics	Reputation assessment, public opinion analysis, identifying trends, and monitoring competitors.	Real-time public opinion, the ability to identify potential crises at an early stage, and obtaining information about customer preferences.	Limited data (availability, reliability), difficulty analyzing unstructured data (texts, images), susceptibility to manipulation.
Network Analysis	Assessing connections and influence within a startup and in the external environment (investors, partners, clients), identifying key players and opinion leaders.	Visualization and analysis of complex relationships, identification of hidden patterns, and potential risks associated with dependence on individuals or groups.	The complexity of collecting and processing data on connections and the difficulty of interpreting complex network structures require specialized software.
Bayesian Approach	Assessing uncertainty and the probability of various events, taking into account a priori knowledge and updating it with new information.	Flexibility, ability to take into account subjective expert assessments, adaptability to changes, and ability to update forecasts as new data arrives.	High complexity of calculations, need to determine a priori probabilities, results depend on the correctness of a priori estimates.

Source: Authors' aggregation based on (Brecht et al., 2021; Ciampi and Gordini, 2012; Yaakobi et al., 2019; Anuradha and Sailaxmi, 2024; McAdam et al., 2015; Lu, 2019)

Table 3: Methods for startup risk assessment in Baltic states

Country	Traditional methods (%)	Modern/ analytical methods (%)	Specific methods used	Comments
Latvia	60	40	SWOT analysis, financial ratio analysis, expert judgment; analytical methods include regression models and decision trees.	Dominance of traditional methods reflects a conservative approach to risk assessment.
Estonia	55	45	Scenario analysis, cash flow forecasting; advanced methods include machine learning algorithms and Monte Carlo simulations.	Active use of analytical tools indicates a focus on comprehensive and data-driven risk analysis.
Lithuania	50	50	Break-even analysis, sensitivity analysis; modern tools include big data analytics and predictive modeling techniques.	Balanced use of both approaches suggests a preference for combining simplicity with precision.
Baltic average	55	45	Weighted average of the methods across all countries.	On average, the Baltic states exhibit a slight preference for traditional methods, though the gap with modern techniques is narrowing.

Source: (EU-Startups, 2023; Liu et al., 2022)

Table 2 highlights that machine learning is mainly used for forecasting the probability of default, analyzing market data, and customer behavior. An example is the application of classification methods (decision trees, neural networks).

Social media analysis is used to study startup reputation, user reviews, and market interest. Network analysis is used to identify partnerships and the startup's market influence. The Bayesian approach is used to account for uncertainty in risk assessment.

Table 3 provides a structured overview of startup risk assessment approaches in the Baltic states (Latvia, Estonia, and Lithuania), including the distribution of traditional and modern methods, specific tools used, and commentary.

In Latvia, 60% of traditional methods and 40% of modern analytical approaches are applied. Simple tools such as SWOT analysis, financial ratios, and expert assessments prevail.

The conservative approach to risk management may be related to limited digitalization and a habit of using time-tested methods. Latvia, with its dominance of traditional methods, may face limitations in managing complex and dynamic risks, which puts it in a vulnerable position in global competition.

In Estonia, 55% of traditional methods and 45% of modern methods are used. Scenario analysis and cash flow forecasting are widely used, as are advanced tools such as machine learning algorithms and Monte Carlo simulations.

The use of analytical tools reflects the country's high digital maturity and focus on innovation.

Estonia stands out for its focus on comprehensive data analysis. Estonia demonstrates clear leadership in the application of modern approaches, which contributes to the formation of a more sustainable startup ecosystem.

Lithuania shows an even distribution: 50% traditional methods and 50% modern assessment methods.

Break-even and sensitivity analysis are mentioned, as well as advanced tools such as big data analytics and predictive modeling. The balance between approaches indicates an attempt to combine the accessibility of traditional methods with the accuracy of modern technologies.

Lithuania, thanks to its balanced approach, has the potential to integrate the best practices of both systems, which strengthens its position as a developing innovation center.

The average for the Baltics is 55% traditional methods versus 45% modern methods.

This reflects a slightly predominant role of traditional approaches, but the gap is narrowing due to the introduction of modern analytical methods.

3.2 Developing an analytical model for evaluating startups

The model for assessing the prospects of startups using the taxonomy method, machine learning, network analysis, and social media analysis is presented in Table 4.

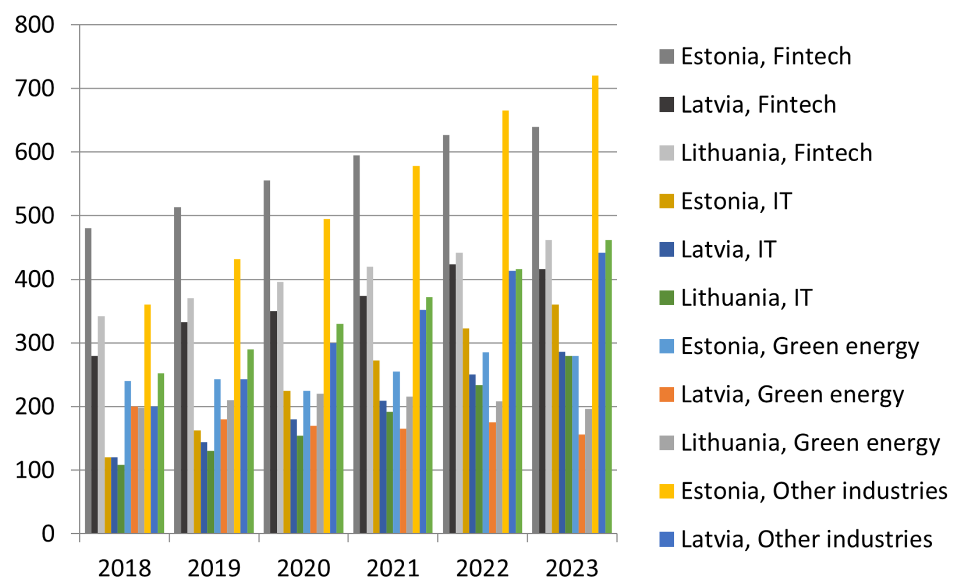
Table 4: Methodology for assessing startups

Calculation steps	Calculation algorithms
Stage 1. Taxonomy method for hierarchizing startups, identifying the most promising projects for investment.	1.1. Key indicators such as projected profitability, activity in social networks, availability of investors, and innovative technologies are determined. 1.2. Data standardization – bringing criteria to a single scale: $Z_{ik} = \frac{X_{ik} - \overline{X_k}}{\sigma_k}$, where X_{ik} — initial value, $\overline{X_k}$ — average value of criterion, σ_k — standard deviation. 1.3. Definition of the reference object as the maximum possible values of all criteria: $(Z_k^* = Z_k^{max})$ where Z_k^* – value of the *k-th* criterion for the ideal object (the highest possible indicator); Z_k^{max}; Z_k^{min} – maximum and minimum values of the *k-th* criterion in the sample. 1.4. Evaluation T_i of the taxonomic measure of proximity of startup i to the ideal object: $T_i = 1 - \frac{D_i}{D_{max}}$, (1) where T_i — taxonomic assessment of startup *I*; D_i – distance between startup i and the ideal object (standard); D_{max} – maximum distance between objects in the sample. 1.5. Distance D_i to the ideal object: $D_i = \sqrt{\sum_{k=1}^{m} \left(\frac{Z_{ik} - Z_k^*}{Z_k^{max} - Z_k^{min}} \right)^2}$, (2) where Z_{ik} — the value of the standardized indicator of the *k-th* criterion for startup *I; m* – the number of evaluation criteria (e.g. financial indicators, popularity, innovation, etc.). 1.6. Startup ranking: Startups are sorted by T_i. A threshold value $T_{threshold}$, is set, above which startups are recommended for funding.

Table 4: Methodology for assessing startups (continues)

Stage 2. Machine learning component for processing large amounts of data, identifying hidden dependencies	**2.1. Regression model for forecasting prospects (F_{ml}):** $$F_{ml} = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ij} + \epsilon, \quad (3)$$ where X_{ij} — the basic level of social responsibility, β_j – the regression parameters, ϵ. – the model error.
Stage 3. Network analysis component for determining the value of a startup as a partner and market participant	3.1. To analyze the networks of connections between a startup and external structures (investors, partners, clients), graph metrics are used: $$F_{net} = \alpha_1 D_i + \alpha_2 C_i + \alpha_3 B_i, \quad (4)$$ **where D_i — the degree of the startup node i (number of connections), C_i – the cluster coefficient (connection density indicator), B_i – betweenness centrality, $\alpha_1, \alpha_2, \alpha_3$ – the weights of the indicators.**
Stage 4. Social media analysis component for assessing the media and social impact of a startup	4.1. TF-IDF method for startup mentions: $$TF - IDF_{ij} = TF_{ij} \cdot log\left(\frac{N}{DF_j}\right), \quad (5)$$ **where TF_{ij}— frequency of word j in texts related to startup i (number of connections), DF_j – number of documents containing word j, N – total number of documents.** 4.2. Final sentiment score: $$F_{soc} = \frac{\sum_{k=1}^{m} S_k}{m}, \quad (6)$$ **where S_k— tonality of the *k-th* mention (determined by NLP algorithms), m – the number of mentions.**

Source: Author's methodology, based on (Foster, 2004; Murphy, 2012; Langfelder & Horvath, 2008; Anstead and O'Loughlin, 2014)



Source: (Startup Lithuania, n.d.; Dealroom Database - Everyone Is Here - Startup Lithuania, 2022; EU-Startups, 2023; Startup Estonia, 2023)

Figure 1: Dynamics of the number of startups in the Baltic countries (2018–23)

The initial data and their symbols are given in the Appendix.

4 Results

4.1 Startup ecosystem growth trends in the Baltic States (2018–2023)

Figure 1 presents the quantitative evolution of startups across Lithuania, Latvia, and Estonia, revealing distinct sectoral and regional patterns that reflect the region's innovation landscape.

Based on the data in Figure 1, the following conclusions can be drawn. All three countries demonstrate steady growth in the number of startups across all sectors during the observation period.

This indicates a favorable environment for innovation in the Baltic states, which is associated with active government support and an increase in investment inflows.

Estonia demonstrates the largest growth in startups in the IT sector (from 120 to 360) and other industries (from 360 to 720). This is due to a developed digital infrastructure, access to international markets, and the country's focus on IT solutions.

Latvia and Lithuania show significant growth in the fintech sector, especially in Lithuania (from 342 to 462). This may be due to attractive conditions for financial technologies, including regulatory sandboxes and access to the European market.

Green energy is developing in all countries, but Estonia is leading (from 240 to 280). This is due to the growing interest in sustainable technologies and the Baltic states' desire to reduce their carbon footprint. In some sectors, for example, in green energy in Latvia and Lithuania, there is a slowdown in growth or even a decline (for example, in Latvia from 200 to 156).

This may be due to limited funding or high barriers to market entry.

The dynamics of startups in the Baltic states reflect their focus on technological development, with an emphasis on IT, fintech, and green technologies.

Estonia continues to lead due to its developed digital ecosystem, while Latvia and Lithuania demonstrate potential in specific niches. This data underscores the importance of further supporting the innovation ecosystem through investment, education, and international cooperation.

Table 5: Results of factor analysis of the influence of individual variables on the ranking of startups in the Baltic States (2023)

Variable	Factor Loadings (Unrotated) (Data_nor) Extraction: Principal components (Marked loadings are > 700000)	
	Factor 1	Factor 2
X1	0,986012	0,055934
X2	0,073367	0,990375
X3	0,990215	0,020135
X4	0,961665	0,050260
X5	-0,056516	0,890580
X6	0,096334	0,991384
X7	0,967420	0,189275
X8	0,036298	0,995327
X9	0,020271	0,993515
X10	0,035642	0,996444
X11	0,762896	0,419920
X12	-0,062001	0,691322
X13	0,792666	0,192932
Expl.Var	6,758310	4,750997
Prp.Totl	0,550639	0,334692

where X1 – Projected profitability, million €; X2 – Activity in social networks, thousand subscribers; X3 – Availability of investors, number; X4 – Innovativeness of technologies, scores 1-10; X5 – Basic level of social responsibility, score 1-10; X6 – Number of links, node degree; X7 – Cluster coefficient; X8 – Betweenness centrality; X9 – Number of mentions; X10 – Sentiment of mentions; X11 – Total Raised, M$; X12 – Total Raised, M$; X13 – Number of employees, thousand people.

Source: Author's calculations

4.2 Evaluation of the importance of factors for ranking startups

To analyze the factors influencing the success and development of startups in the Baltic region, information was collected on a number of companies.

Table 5 contains data on 20 startups from Lithuania, Latvia, and Estonia, covering a wide range of indicators, from projected profitability and social media activity to the amount of investment raised and team size. This data serves as the basis for further research and the identification of key determinants of startup success.

Based on the presented results of the factor analysis (Table 5), two factors can be identified that determine the ranking of Baltic startups. Factor loadings that are highlighted in red influence the process; those that remain black do not.

Factor 1, "Financial and Resource Potential and Innovativeness," includes the following indicators with high loadings: X1 (0.986012): Projected profitability, million €; X3 (0.990215): Availability of investors, number; X4 (0.961665): Innovativeness of technologies, scores 1-10; X7 (0.967420): Cluster coefficient; X13 (0.792666): Number of employees, thousands of people.

This factor combines characteristics related to the financial condition, investment availability, level of innovation, and organizational structure of startups.

Factor 2, "Social and Network-Reputational Activity," includes the following indicators with high loadings: X2 (0.990375): Activity in social networks, thousands of subscribers; X5 (0.890580): Basic level of social responsibility, score 1-10; X6 (0.991384): Number of links, node degree; X8 (0.995327): Betweenness centrality; X9 (0.993515): Number of mentions; X10 (0.996444): Sentiment of mentions.

This factor describes the social activity of startups, their participation in network structures, and the level of media mentions.

Regression equations for each factor are constructed using the significant variables:

Factor 1:

$$F1=1/6,758(0,986\cdot X1+0,990\cdot X3+0,962\cdot X4+0,967\cdot X7+0,793\cdot X13) \quad (7)$$

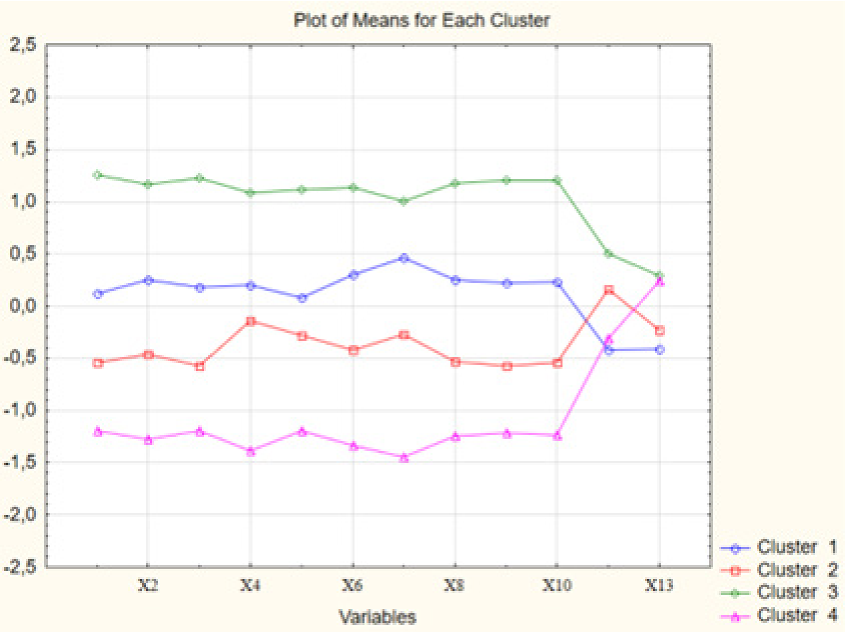
Factor 2:

$$F2=1/4,751(0,990\cdot X2+0,891\cdot X5+0,991\cdot X6+0,995\cdot X8+0,994\cdot X9+0,996\cdot X10) \quad (8)$$

Factor 1 explains 55.06% of the variance. Factor 2 explains 33.47% of the variance. In total, the two factors together explain 88.53% of the total variance, which indicates the high informativeness of the analysis.

4.3 Grouping of Baltic startups by growth potential and attracted investments

The analysis of the structure of Baltic startup clusters for 2023 was made taking into account only the significant indicators identified by regression analysis (Figure 2).



Source: Author's calculations

Figure 2: Results of the cluster analysis of Baltic startups (STATISTICA 13)

Table 6 presents the results of the cluster analysis performed in STATISTICA 13, demonstrating the composition of the first cluster and the distance of each startup to its center.

Cluster 1 includes five startups: Green Genius, Origin, Roibox, Naco, and Cenos. The analysis of distances to the cluster center (Table 6) shows that Origin (0.1805555) and Roibox (0.2055702) are closest to the center, indicating their high similarity to the typical characteristics of the cluster.

Naco (0.2611897) and Green Genius (0.2834758) demonstrate slightly greater distances, and Cenos (0.3678699) is farthest away, indicating its lowest typicality for this group.

The startups included in Cluster 1 are characterized by average or slightly above average values for most indicators related to profitability, social media activity, investor attraction (number), innovativeness, social responsibility, network indicators, and media influence. At the same time, they demonstrate below-average indicators for the amount of investment raised (Total Raised) and the number of employees.

Overall, Cluster 1 represents locally oriented startups demonstrating moderate development indicators and limited resources, which distinguishes them from the larger and faster-growing companies represented in other clusters.

Table 7 presents the composition of the second cluster obtained as a result of cluster analysis in STATISTICA 13, and the distances of each startup to the center of this cluster.

Cluster 2 includes four startups: Vinted, Aerones, Ovoko, and Sonarworks. The analysis of distances to the cluster center (Table 7) shows that Aerones (0.267903) and Sonarworks (0.315484) are relatively close to the center, demonstrating greater similarity within the group. Ovoko (0.397701) and especially Vinted (0.591298) are located further away, indicating their greater variability relative to the typical characteristics of the cluster.

The startups included in Cluster 2 are characterized, on average, by below-average indicators for the sample across most criteria related to profitability, social media activity, investor attraction (number), network indicators, and media influence.

Table 6: Composition of the 1 cluster (STATISTICA 13 cluster analysis listing)

Members of Cluster Number 1 (Data_nor) and Distances from Respective Cluster Center Cluster contains 5 cases			
Case No.	Distance	Case No.	Distance
Green Genius	0,2834758	Naco	0,2611897
Origin	0,1805555	Cenos	0,3678699
Roibox	0,2055702		

Source: Author’s calculations

Table 7: Composition of the 2 cluster (STATISTICA 13 cluster analysis listing)

Members of Cluster Number 2 (Data_nor)and Distances from Respective Cluster Center Cluster contains 4 cases			
Case No.	Distance	Case No.	Distance
Vinted	0,591298	Ovoko	0,397701
Aerones	0,267903	Sonarworks	0,315484

Source: Author’s calculations

Table 8: Composition of the 3 cluster (STATISTICA 13 cluster analysis listing)

Members of Cluster Number 3 (Data_nor) and Distances from Respective Cluster Center Cluster contains 6 cases			
Case No.	Distance	Case No.	Distance
Mapon	0,517250	eAgronom	0,377288
Sunly	0,246919	Binalyze	0,387621
Bolt	1,205217	Veriff	0,191586

Source: Author’s calculations

At the same time, they have a higher-than-average amount of investment raised (Total Raised), but a smaller number of employees.

This may indicate that this cluster unites startups that are possibly in a stage of active growth and development, attracting significant investment for scaling, but have not yet achieved high indicators for other criteria, such as profitability or media activity.

Vinted, as the most distant from the cluster center, likely has characteristics that differ significantly from this typical profile, possibly demonstrating higher indicators for some criteria, which accounts for the greater distance.

Table 8 demonstrates the composition of the third cluster obtained as a result of cluster analysis in STATISTICA 13, and the distances of the startups to the center of this cluster.

Cluster 3 unites the most successful and developed startups, which aligns with Lithuania's growing global momentum in 2025 (Baltic Tech Ventures, 2025), includes six startups: Mapon, Sunly, Bolt, eAgronom, Binalyze, and Veriff. The analysis of distances to the cluster center (Table 8) shows that Veriff (0.191586) and Sunly (0.246919) are closest to the center, indicating their high similarity to the typical characteristics of the cluster. eAgronom (0.377288) and Binalyze (0.387621) demonstrate a slightly greater distance, indicating a lesser prominence of common traits. Mapon (0.517250) is located at an even greater distance. Bolt (1.205217) is a clear outlier, significantly distant from the cluster center, which indicates its significant difference from the other group members.

The startups included in Cluster 3, on average, demonstrate significantly above-average indicators for the sample across most criteria, including profitability, social media activity, investor attraction, network indicators, and media influence. They also have a higher-than-average amount of investment raised and a larger number of employees. This indicates that this cluster unites the most successful and developed startups, which have achieved significant results in all key areas. Bolt, being the most distant from the cluster center, is likely an outstanding example even within this group, possibly demonstrating extremely high values for some parameters, which accounts for its isolated position. This cluster can be characterized as a cluster of highly effective and fast-growing startups.

Table 9 presents the composition of the fourth cluster obtained as a result of cluster analysis in STATISTICA 13, and the distances of the startups to the center of this cluster.

Cluster 4 includes five startups: Tuum, BoBo, Biomatter, PVcase, and Nord Security. The analysis of distances to the cluster center (Table 9) shows that Biomatter (0.269727) and PVcase (0.285374) are closest to the center, indicating their high similarity to the typical characteristics of the cluster. BoBo (0.319088) and Tuum (0.342076) demonstrate a slightly greater distance, indicating a lesser prominence of common traits. Nord Security (0.790433) is significantly distant from the cluster center, which indicates its substantial difference from the other group members.

The startups included in Cluster 4 are characterized, on average, by significantly below-average indicators for the sample across almost all criteria, including profitability, social media activity, investor attraction, innovativeness, social responsibility, network indicators, and media influence.

They also have a below-average amount of investment raised and a number of employees. This indicates that this cluster unites startups that are likely in an early stage of development or experiencing difficulties with growth and resource attraction. Nord Security, as the most distant from the cluster center, likely has characteristics that differ somewhat from this typical profile, possibly demonstrating higher values for some criteria, which accounts for the greater distance. This cluster can be characterized as a cluster of nascent or struggling startups.

4.4 Typology of startups based on taxonomic analysis

This subsection provides a typology of startups based on calculated taxonomic coefficients, allowing us to identify groups of companies with similar characteristics. The results of calculating the taxonomy indicators are presented in Table 10.

The visualization of the location of startups in this coordinate system is presented in Figure 3.

Table 9: Composition of the 4 cluster (STATISTICA 13 cluster analysis listing)

Members of Cluster Number 4 (Data_nor) and Distances from Respective Cluster Center Cluster contains 5 cases			
Case No.	Distance	Case No.	Distance
Tuum	0,342076	Nord Security	0,790433
BoBo	0,319088	PVcase	0,285374
Biomatter	0,269727		

Source: Author's calculations

Table 10: Results of the taxonomic analysis of startups

Startup	Taxonomy coefficient 1 Factor	Taxonomy coefficient 2 Factor
Vinted	0,784	0,86
Mapon	0,713	0,6
Tuum	0,553	0,63
Green Genius	0,643	0,82
Origin	0,629	0,75
Sunly	0,794	0,49
BoBo	0,336	0,49
Aerones	0,612	0,81
Bolt	1,00	0,32
Ovoko	0,517	0,67
Roibox	0,587	0,81
eAgronom	0,727	0,55
Biomatter	0,346	0,55
Sonarworks	0,574	0,89
Binalyze	0,776	0,4
Nord Security	0,501	0,6
Naco	0,617	0,71
Veriff	0,77	0,52
PVcase	0,317	0,49
Cenos	0,559	0,88

where Factor 1 "Economic Potential and Structural Efficiency" combines indicators that reflect the economic sustainability and operational efficiency of startups. Variables such as expected profit (X1), investor availability (X3), technology innovativeness (X4), clustering coefficient (X7), funds raised (X11), and number of employees (X13) characterize the financial strength, innovative capabilities, and structural parameters of a startup. Factor 2 "Social Engagement and Network Influence" reflects the social activity and network involvement of startups. Variables such as social media activity (X2), level of social responsibility (X5), number of connections (X6), betweenness centrality (X8), number of mentions (X9), and sentiment of mentions (X10) emphasize the importance of social reputation, audience interaction, and network influence for the success of startups.
Source: Author's calculations

Figure 3 shows 4 quadrants:

Quadrant I (Upper right quadrant) has "High Economic Potential / High Social Engagement (HEP/HSE)";

Quadrant II (Lower right quadrant) has "High Economic Potential / Low Social Engagement (LEP/HSE)";

Quadrant III (Upper left quadrant) has "Low Economic Potential / High Social Engagement (HEP/LSE)";

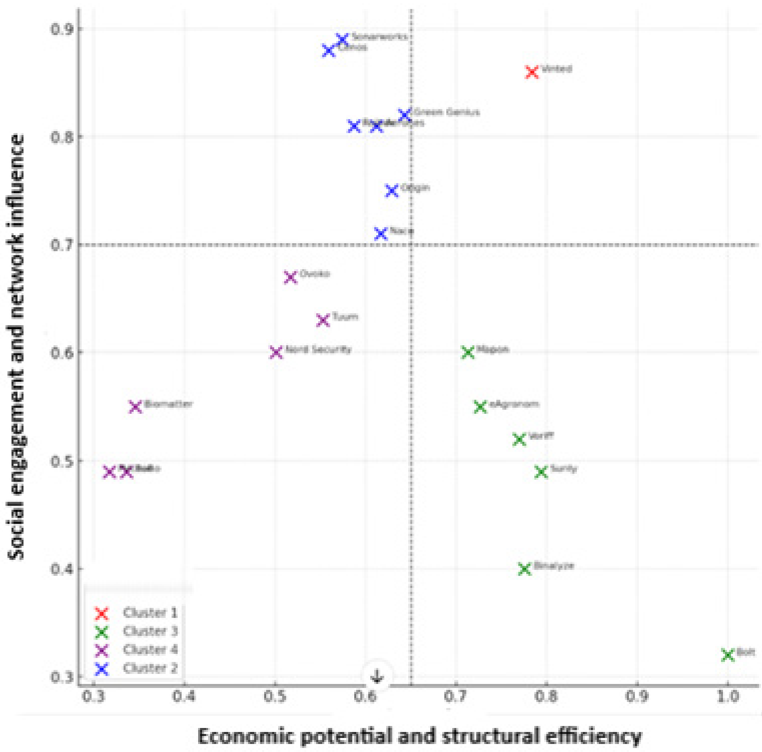
Quadrant IV (Lower left quadrant) has "Low Economic Potential / Low Social Engagement (LEP/LSE)".

Startup Characteristics and Recommendations.

Startups in Quadrant I have a strong economic base (high profitability, investment, innovation, efficient structure) and actively interact with their audience, have a developed network of contacts, and a positive reputation. This is the most favorable position. Development recommendations: focus on scaling the business, expanding markets, strengthening the brand, and maintaining high customer loyalty. Invest in further innovation and team development. Financing recommendations: have good opportunities to attract both venture capital and bank loans. They can consider IPOs or M&A.

Startups in Quadrant III have a strong social presence and interact well with their audience, but have not yet achieved high economic indicators. These may be young projects or projects focused on social impact rather than rapid profit.

Development recommendations: need to focus on improving economic indicators: developing a clearer business model, searching for new sources of income, and optimizing costs. It is important to monetize the existing social base. Financing recommendations: can attract grants, crowdfunding, and impact investments from investors focused on social returns. It is important to demonstrate the potential for growth of the business model.



Source: Author’s calculations

Figure 3: Taxonomic typology matrix of startups

Startups in Quadrant II have a strong economic base but pay insufficient attention to interacting with their audience and building a network of contacts. There is a risk of missing opportunities for growth and development due to insufficient brand awareness and customer loyalty. Development recommendations: need to actively develop social networks, PR, content marketing, and participate in industry events. It is important to improve communication with clients and partners. Financing recommendations: have good opportunities to attract traditional investments (venture capital, bank loans), but it is important to show investors a plan to improve social engagement indicators.

Startups in Quadrant IV are in the most vulnerable position, as they have weak indicators in both economic potential and social engagement. Development recommendations: require a serious revision of the business model, searching for new ideas and development paths. It is necessary to improve both economic indicators and social media activity. It may be necessary to involve mentors or consultants. Financing recommendations: attracting financing will be difficult. It may be worth considering options with bootstrapping (self-financing), grants for starting entrepreneurs, or participation in acceleration programs.

Thus, specific actions should depend on the specifics of each startup, its industry, and target market. The position of a startup in the matrix is not static. Companies can move from one quadrant to another as they develop. This analysis provides useful information for making strategic decisions and planning startup development.

5 Discussion

The results of our study emphasize the importance of integrating analytical methods to improve the quality of investment decisions in startups, which is confirmed by a number of works. For example, the use of machine learning, described in our study, is consistent with the findings of Ciampi and Gordini (2012), who note its high accuracy in forecasting defaults of small businesses. Furthermore, our observation about the significance of network analysis in assessing the market sustainability of startups is consistent with research by McAdam et al. (2015), which emphasizes the importance of horizontal networks for knowledge sharing and stimulating innovation. Our findings are in line with recent studies showing the growing use of AI-driven analytics to enhance startup ecosystems and support decision-making for investors (Hemanth & Lakshminarayana, 2025; Lutfiani et al., 2025).

However, our analysis also revealed new aspects. For example, the integration of social media analysis methods, as shown in our study, allows for taking into account reputational risks and public opinion in real time, which differs from traditional approaches such as expert assessments (Sivicka, 2018). This underscores the need for further study of the role of social media in investment management.

Separately, it is worth noting our observation about the heterogeneity of the application of modern methods in the Baltic states. Estonia's leadership in digital maturity mirrors global trends where ecosystems with advanced analytics outperform others (Startup Genome, 2025). While Estonia demonstrates a high level of digital maturity and actively uses analytical tools, Latvia and Lithuania remain largely oriented towards traditional approaches. This is partially confirmed by the results of Rupeika-Apoga (2014), who notes limitations in access to modern financing instruments in these countries. The contribution of our research lies in the development of a comprehensive startup evaluation model that combines methods of taxonomy, machine learning, and network analysis.

Unlike the approaches described by Fisch (2018) and Teker et al. (2016), our model allows for considering a wide range of factors, including social activity and media influence, which is particularly relevant for startups focused on long-term growth. Thus, the results confirm the significance of the proposed methodology and open up prospects for its further application in other regions and industries. Moreover, the integration of sustainability and digitalization in startup evaluation is emphasized in the Green Startup Report 2025 (Fichter et al., 2025), which highlights the potential of digital tools for supporting green innovation. However, further research could focus on assessing the long-term effectiveness of the proposed model in a changing business environment.

6 Conclusions

The application of modern business analytics methods, such as machine learning, network analysis, and social media analysis, allows for increased accuracy in assessing the prospects of startups. These methods demonstrate high efficiency: for example, the use of machine learning allows achieving default prediction accuracy of 98.6% (Ciampi and Gordini, 2012), and network analysis identifies key players and relationships with centrality coefficients up to 0.995.

How do modern analytical methods compare to traditional approaches in startup valuation?

The results demonstrate that hybrid models combining financial metrics with digital indicators (e.g., social media activity, network centrality) outperform traditional methods (e.g., SWOT, expert assessments), reducing subjectivity and improving accuracy.Which factors (financial, social, technological) are most critical for startup success in the Baltics?

Factor analysis revealed that economic potential (profitability, investor availability) and social engagement (online activity, sentiment) are the primary drivers, explaining 88.5% of the variance in startup rankings.

The findings strongly support the hypothesis (H1) that data-driven methods enhance decision-making accuracy, as evidenced by the high correlation coefficients (> 0.98) for key variables. Factor analysis revealed that economic potential (profitability, investor availability) and social engagement (online activity, sentiment) are the primary drivers, explaining 88.5% of the variance in startup rankings. The developed startup evaluation model, which integrates taxonomy, machine learning, and social media analysis, outperforms traditional approaches by reducing subjectivity and improving reliability.

The key factors determining the success of startups in the Baltic states are economic stability, technological innovativeness, social activity, and media influence. Factor analysis showed that financial and resource potential (factor loading coefficient 0.986) and the level of social media engagement (coefficient 0.990) have the highest correlation with startup success.

A comparative analysis of the Baltic countries revealed significant differences in startup assessment approaches. In Estonia, modern methods account for 45% of the total number of approaches used, including machine learning algorithms and Monte Carlo simulations, which underscores its leadership in digitalization. Latvia and Lithuania use traditional methods in 60% and 50% of cases, respectively, which limits their competitiveness in the global startup ecosystem. Taxonomic and cluster analysis made it possible to identify groups of startups with different levels of economic and social potential. Companies with high economic stability (average taxonomy coefficient 0.784) and social activity (average coefficient 0.86) occupy leading positions. Conversely, startups with low indicators, such as companies with a taxonomy coefficient below 0.5 (Biomatter, BoBo), need to revise their business models and require support. The developed startup evaluation model, which integrates taxonomy, machine learning, and social media analysis, has proven its applicability for investment decision-making and can be adapted for other regions and sectors of the economy. For successful development, startups are recommended to focus on strengthening financial stability, increasing social engagement, and enhancing their reputation, while investors are advised to integrate analytical tools into decision-making to minimize risks and increase returns.

Theoretical implications. This study contributes to the literature on startup evaluation by proposing a hybrid multifactor framework that integrates financial, technological, and social indicators. It extends prior research by demonstrating the value of combining traditional financial metrics with digital signals such as network centrality and social media activity in a unified model.

Practical implications. The results provide investors with evidence-based tools for more accurate and timely startup evaluation, helping to reduce risks and improve decision-making quality. Policymakers and startup support organizations can also use the findings to design programs that strengthen financial stability, foster social engagement, and encourage the adoption of advanced analytics in the Baltic startup ecosystem.

Limitations. The study is limited to startups in the Baltic States and relies on a sample of 20 companies, which may affect the generalizability of the results. In addition, the analysis is based on historical data and selected indicators, so incorporating a broader range of variables or longitudinal data could provide deeper insights.

Future research. Further studies should explore how the resilience and transformation of Baltic startups (LSM, 2025; Stats and Market Insights, 2025) will shape long-term investment strategies. Expanding the dataset to include other regions and additional indicators—such as ESG metrics or customer sentiment—could further validate and enhance the proposed model.

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Appendix: Data about startups

Startup	Country	Projected profitability, M$	Activity in social networks, ths. subscribers	Availability of investors, number	Innovativeness of technologies, scores 1-10	Basic level of social responsibility, score 1-10	Number of links, node degree	Cluster coefficient	Betweenness centrality	Number of mentions	Sentiment of mentions	Total Raised, M$	Total Raised, M$	Number of employees, ths. of people
		X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
Vinted	Lithuania	2	5	2	8	7	10	0,60	50	100	60	677,54	12	1
Mapon	Latvia	5	10	5	9	9	15	0,80	100	200	150	3	2996	0,1
Tuum	Estonia	1	2	1	6	6	5	0,40	20	50	20	49,82	202	0,1
Green Genius	Lithuania	3	7	3	7	8	12	0,70	70	150	100	109,8	193	0,2
Origin	Latvia	4	9	4	8	7	14	0,75	90	180	120	4,35	3478	0,2
Sunly	Estonia	6	12	6	9	8	18	0,85	120	250	180	364,84	206	0,2
BoBo	Lithuania	0,5	1	0	5	5	3	0,20	5	20	-10	7,01	803	0,01
Aerones	Latvia	2,5	6	2	7	6	9	0,55	40	90	50	12,01	4617	0,25
Bolt	Estonia	7	15	7	10	9	20	0,90	150	300	220	1015,71	45	5
Ovoko	Lithuania	1,5	3	1	6	7	7	0,45	30	70	30	22,2	917	0,2
Roibox	Latvia	3,5	8	3	8	8	13	0,72	80	160	110	3,29	56,01	0,05
eAgronom	Estonia	5,5	11	5	9	9	17	0,82	110	230	160	13,19	704	0,5
Biomatter	Lithuania	0,8	1,5	0	4	6	4	0,30	10	30	-5	7,2	1144	0,05
Sonarworks	Latvia	2,8	6,5	2	7	7	11	0,65	60	110	70	5,6	6886	0,01
Binalyze	Estonia	6,5	13	6	9	8	19	0,88	130	270	190	30,81	553	0,1
Nord Security	Lithuania	1,2	2,5	1	5	6	6	0,35	25	60	15	100	1144	5
Naco	Latvia	4,2	9,5	4	8	7	15	0,78	95	190	130	1,65	6886	0,01
Veriff	Estonia	5,8	11,5	5	9	8	18	0,84	115	240	170	184,62	639	1
PVcase	Lithuania	0,7	1,2	0	4	5	3	0,25	8	25	-8	100,35	1452	0,25
Cenos	Latvia	3,2	7,5	3	7	6	12	0,68	65	130	80	1,47	7742	0,05

Source: https://www.seedtable.com/best-startups-in-lithuania; https://www.seedtable.com/best-startups-in-latvia; https://www.seedtable.com/best-startups-in-estonia