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Development of a Methodology Based on Fuzzy Logic for Solving the Problem of Evaluating a Startup Team Under Uncertainty

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Aim/Purpose: The purpose of the article is to develop a methodology for evaluating startup teams and to create a corresponding computer model based on multicriteria analysis and fuzzy-logic decision-making. Particular attention is paid to determining both qualitative and quantitative characteristics of the team, and obtaining a generalized integral assessment of the startup team under uncertainty.
Design/methodology/approach: An integrated evaluation method is proposed that combines the principles of the fuzzy set approach and expert evaluation and is implemented as a fuzzy inference system in MATLAB. The developed model used different initial characteristics of the startup team as input parameters. For this, formulas were identified, described, and utilized to calculate the values of these evaluation parameters. The set of linguistic variables and a system of rules for processing fuzzy data were defined. Literature data, expert and investor assessments, and case studies of real startup projects served as the empirical basis for the study.
Findings: The results demonstrate that the proposed approach enables a fairly objective and comprehensive assessment of a startup team's quality, considering multiple assessment criteria, their interrelationships, and the combination of qualitative and quantitative input data, all within the context of significant uncertainty. The methodology ensures the objectivity and repeatability of the assessment, making it a valuable decision-support tool for various situations and participants within the startup community.
Research implications/limitations: The study is limited by the amount of data on real startup teams for model verification, which leaves much to be desired, as well as the need for further empirical substantiation and adjustment of the fuzzy model as a whole, including formulas for input parameters, linguistic variables, and decision rules, based on expert opinions. Possible areas for further research include adapting the method to different stages of startup development, taking into account their field of activity, size, and other specific features, and enabling more accurate model adjustment across various practical cases.
Originality/value/contribution: The article's originality lies in integrating fuzzy logic with multicriteria analysis to assess the human factor in startups. A useful contribution involves creating a practice-oriented tool that enhances the accuracy and reliability of team analysis, which is essential for startups themselves, business angels, venture funds, accelerators, and other participants in the startup community.

Keywords: Startup team evaluation, Fuzzy evaluation methodology, Team scoring model

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1 Introduction

1.1 Place of characteristics of quality, level, and team strength in the overall startup assessment

Assessing the quality and level of a startup team is a core element of venture expertise and the strategic analysis of innovative projects. In contexts marked by high uncertainty, limited revenue stability, and dynamic market conditions, Berman et al. (2024) suggest that team-related factors can be particularly influential in determining early-stage startup outcomes.

The startup team constitutes the project's core human capital, encompassing competencies, experience, motivation, and managerial capabilities. In this regard, Knight et al. (2020) and McCarthy et al. (2023) note that a team's capacity to adapt to external changes, the quality of managerial decision-making, and its ability to scale growth are closely associated with the degree of team balance, members' professional qualifications, entrepreneurial mindset, and effectiveness of internal interaction.

Empirical research in the field of entrepreneurship confirms that high-quality teams have a higher resistance to failure, reach the product-market fit stage faster, use resources more efficiently, and attract investments more often. Moreover, investors and acceleration programs systematically include team assessment as one of the main factors when selecting startups, since even a strong idea loses practical value if poorly implemented.

Key parameters commonly used to assess the level of a startup team include the presence of relevant industry experience, managerial and technical competencies, the degree of motivation and involvement, role distribution and functional balance, leadership and strategic vision, as well as prior collaboration history and performance indicators, as outlined by González et al. (2024).

Together, these characteristics enable us to draw conclusions about the team's capacity to cope with growth challenges, overcome crises, and interact effectively with external stakeholders. Thus, assessing the level of a startup team is not a secondary element of analysis, but rather a critical tool for predicting the success of an innovative enterprise, especially in the phase before achieving a sustainable business model and profitability.

1.2 The importance of assessing the startup team quality for participants in the startup ecosystem

Evaluating the quality and caliber of a startup team is a crucial aspect of analysis for all key stakeholders in the startup ecosystem. In the early stages of a startup's development, when the product is not yet complete and the business model is still evolving, the team becomes the primary asset that determines the project's success. Different players in the startup ecosystem, including investors, accelerators, government funds, corporate partners, potential employees, analysts, and even end users, evaluate the team based on their specific goals and risks.

For investors, including venture funds, business angels, and corporate venture arms, the startup team is often considered a key factor in investment decisions. According to Silva et al. (2024) and Li et al. (2024), because startups frequently undergo strategic or product changes, the capabilities of the team's human capital—such as adaptability, learning capacity, execution, and scalability—may strongly influence outcomes. Investors tend to consider professional experience, entrepreneurial orientation, leadership skills, and the potential for effective team synergy.

Evaluators often consider whether a startup team can execute its strategy, withstand market and investor pressures, and maintain the potential for future financing rounds. According to Berna et al. (2024), accelerators and incubators - tasked with distributing limited resources among many applicants - tend to concentrate on team characteristics, including readiness for intensive work, openness to feedback, rapid hypothesis testing, and full participation by all team members.

The successful completion of the acceleration program largely depends not on the idea itself, but on the quality of the team and its ability to quickly learn and make informed decisions.

State and quasi-state support institutions, including innovation funds and development agencies, often assess whether a startup team uses allocated resources responsibly, advances the project toward commercialization, and contributes to technological and economic value. Schulte and Birkenmeier (2024) suggest that these evaluations tend to emphasize the team's relevant experience, managerial maturity, and prior implementation record.

Corporate partners involved in open innovation, piloting, and technology integration programs evaluate the team as a potential solution provider. In the context of corporate standards and reliability requirements, process maturity, technological competence, transparent communication, and the ability to flexibly adapt become critical. The level of trust within the team becomes crucial for the successful launch of joint projects. According to Aryadita et al. (2023), prospective co-founders and key employees tend to consider the quality of the team and its leadership when deciding whether to join a startup. Issues of compatibility, trust, shared values, and confidence in the project's future directly depend on the strength and stability of the existing team. A high level of competence and cohesion acts as a marker of reliability and prospects.

For analysts, market researchers, and specialized media, the team also plays a key role. In the early stages, the founders' personalities become the focus and shape perceptions of the startup as a stable or, conversely, a weak player in the market. Charisma, reputation, history of previous projects, and the ability to convincingly convey the vision are key factors that attract media and expert interest. Even end users, especially in the B2B segment, build trust in the product through interactions with the team. Flexibility, professionalism, openness to feedback, and speed of response become criteria of reliability, especially when the product itself is still unstable and in need of improvement. The team is perceived as a guarantee of development, support, and long-term value.

The assessment of a startup team's quality and level is widely regarded as a universal and cross-cutting element of analysis within the startup ecosystem. Assenova and Chang (2023) and Blume and Hsueh (2023) suggest that such evaluations can influence the decisions of a range of stakeholders, from investors to potential team members. In addition, Esen et al. (2023) and Mueller (2024) note that team assessment often serves as an indicator of a project's viability, its capacity for growth and adaptation, and its ability to interact effectively with the environment. The team is not merely a group of individuals executing an idea; it is a system-forming element, essential for sustaining progress under conditions of high uncertainty and competition.

1.3 Standard Components and Variables for Startup-Team Evaluation

The assessment of a startup team, drawing on insights from the scientific and venture literature, may be understood as comprising a set of interrelated components, each reflecting critical aspects of entrepreneurial potential. Takas et al. (2025) and Jáki et al. (2022) appear to indicate that these components can serve as a useful framework for evaluating the team's readiness and capabilities. Among these components, the level of professional competence and relevant experience of team members appears to be particularly important. This may include entrepreneurial experience, such as involvement in prior projects—both successful and unsuccessful—as well as technical, industry-specific, and managerial skills, ideally complemented by suitable educational qualifications.

An equally important variable is the team structure in terms of functional diversification and balance. Successful startups are typically built around teams with complementary competencies, ranging from product development and marketing to financial and strategic management, with clearly defined roles (leadership, execution, analytics). Such internal complementarity enables prompt, flexible task implementation.

Particular attention is often given to the quality of team dynamics, including the ability to interact productively, mutual trust, established communication channels, and a history of effective collaboration, all of which may influence the team's level of synergy and internal resilience under conditions of uncertainty and high pressure. For example, Berman et al. (2024) seem to indicate that strong leadership and strategic vision may be regarded as relevant aspects of team effectiveness, encompassing the capacity of one or more team members not only to formulate long-term goals but also to communicate them externally, potentially encouraging both the team and relevant stakeholders to pursue desired outcomes. Execution ability, expressed in the speed and quality of task implementation, is also a key indicator. In particular, the assessment focuses on metrics such as time-to-market for the Minimum Viable Product, the number of product iterations before entering the market, and the alignment of actual actions with set goals under limited resources.

A key factor in a team's resilience is often the level of motivation and involvement of its members. Knight et al. (2020) note that this aspect can be reflected in personal commitment to the project idea, equity among team members, the average work intensity (e.g., hours per week), and the willingness to participate in the project over the long term. High motivation may be positively associated with the team's endurance and its potential to navigate crisis phases during development.

Finally, considerable attention is paid to the team's ability to attract external resources, including investments. Here, the charisma of leaders, public speaking and negotiation skills, and the ability to build trust with investors and partners are crucial. Media coverage and reputational capital are also considered additional indicators of the project's potential investment attractiveness. Thus, the combined assessment of the listed characteristics allows us to form a holistic view of the team's potential as a key factor in the success of a startup in the early stages of its life cycle.

1.4 Methods of Teams evaluation

Scientific and applied literature on startup evaluation emphasizes that the team is one of the most critical success factors, especially in the early stages of project development. In this regard, several methodological approaches to assessing the quality and potential of startup teams have been developed and applied. These methods differ in their structure, depth of analysis, applicability to various stages of startup development, level of subjectivity, and associated costs. Therefore, it is advisable to consider some well-known approaches, indicating their advantages and limitations.

Expert (qualitative) evaluation is perhaps the most common in venture practice. It is based on the subjective conclusions of experienced investors, mentors, consultants, or accelerator managers. The evaluation is based on interviews, personal meetings, observation of team interactions, analysis of participants' resumes and portfolios, and general "intuition" regarding the team's potential. Typically, the focus is on parameters such as professional and entrepreneurial experience, level of competence, team integrity and cohesion, motivation, communication skills, and management potential.

The advantages of this approach may include high flexibility and the ability to adapt to the specifics of a given project, taking into account contextual and individual factors while drawing on the expert's practical experience. At the same time, Franke et al. (2008) noted potential limitations, including considerable subjectivity, limited reproducibility and transparency, and the possibility of cognitive or behavioral distortions influencing the expert's judgment.

Another approach to startup evaluation involves standardized checklists and assessment matrices, commonly referred to as structured frameworks, as noted by Antunes et al. (2021). Tools such as the Team Assessment Matrix, the Founder VC Fit Matrix, venture fund scorecards, and methods that adapt elements of SWOT analysis to human capital could provide a structured framework for incorporating specific parameters and scales, potentially formalizing and systematizing the evaluation process.

Their advantages include standardized procedures, the ability to compare multiple teams, ease of use, and documentation. Among the disadvantages are the superficiality of the analysis in complex cases and limited sensitivity to "soft" factors (for example, emotional intelligence, charisma). Sometimes the formal approach can ignore hidden dynamics.

Behavioral and operational indicators are also used. These approaches often emphasize objective, quantitatively measurable indicators, with examples of metrics including the speed of bringing an MVP to market, the number of product iterations before launch, the volume of team member involvement (including ownership shares in the company), weekly working hours, resistance to deadlines, and flexibility in adapting the strategy, which may be considered as highlighted by Ven et al. (2023).

Among the advantages are high objectivity, the ability to track dynamics over time, and convenience for analytical reporting and decision-making. Among the disadvantages are inapplicability at the pre-seed stage, when data is missing, the risk of overlooking qualitative characteristics, and the potential to erroneously account for formal activity rather than real efficiency.

The psychometric and sociometric approach, also known as Team Psychology Diagnostics, may be a relevant tool for evaluating startup teams, as noted by Fukuzaki and Iwata (2024). This approach uses methods for assessing the team's role structure (e.g., Belbin Team Roles), personality profiles (MBTI, Big Five), motivational drivers, and group dynamics. Behavioural interviews, team compatibility tests, conflict potential analysis, and leadership characteristics are often used. In this case, the advantages include a deep understanding of internal interactions, the ability to identify potential risks (such as conflicts and demotivation), and assistance in selecting and forming effective teams. At the same time, the disadvantages include high labor intensity and demanding qualifications of specialists, possible resistance from participants (unwillingness to "be tested"), and not always correct application outside the coaching context.

Recently, the analysis of digital traces and behavioural analytics (Digital Footprint & Behavioral Data Analysis) has been increasingly used. Modern technologies enable the analysis of startup teams' digital activity. As discussed by Howison et al. (2019), such analysis may include indicators such as the number of GitHub commits, the frequency of Slack communication, activity on LinkedIn, participation in professional communities, and the use of task management systems such as Jira or Trello. This type of data can be used to indirectly assess levels of involvement, discipline, process transparency, and professional activity. Among the advantages of this approach are the potential for automation and scalability, its suitability for continuous monitoring, and its reliance on observed behavioral patterns. At the same time, this method is associated with ethical and legal considerations, including issues related to personal data collection, as well as limitations of interpretation, since digital activity does not necessarily reflect the quality of decision-making. In addition, its effective application may require supplementary tools and analytical resources.

Finally, combined methods are used. Modern practice uses mixed models that integrate qualitative and quantitative approaches, expert judgment, and standardized assessment tools. Such models are described in the literature by Wei (2025) and include multi-criteria team assessment frameworks, internal scoring systems within venture funds, and acceleration-focused due diligence structures. Their advantages include greater assessment validity, the ability to cross-check data, and flexibility and adaptability. However, this requires careful validation and coordination of methodological approaches. It is also noted that they are time and resource-intensive and require a fairly high level of analytical culture.

Thus, assessing startup teams is a complex, multi-level task that requires a combination of quantitative and qualitative methods. There is no universal method suitable for all types of startups and development stages. However, the use of combined approaches, with a focus on the context of the project, the specifics of the industry, and the objectives of the analysis, allows us to significantly increase the reliability and usefulness of the data obtained, which is especially important in investment selection, acceleration, and strategic planning for the development of innovative projects.

So, the main gap in research, which the presented methodology aims to address, is the underdeveloped methods and models for multi-criteria assessment of the quality of startup teams in conditions of unclear, insufficient, or vague information about them.

1.5 The goals of the study

The Research presented below had three main aims and objectives.

First, to study the state of the issue of evaluating a startup team and to identify the main criteria, parameters, and initial variables for such evaluation.

Second, to determine possible mathematical formulas and their components for obtaining numerical measurements of the initial evaluation parameters and to discuss their elements, as well as to develop a structure that allows integrating the initial parameters into a common model for further consistent obtaining of a numerical value for a generalized, integral evaluation.

And third, to analyze the feasibility of using fuzzy modeling, specifically fuzzy interference systems, to create such a model and then develop a basic system using specialized software.

Thus, the aim of the article is to address the research problem of developing and formalizing a methodology for evaluating startup teams using fuzzy logic and to construct a corresponding computational model.

1.6 Brief structure of the article

The manuscript consists of four main parts. In the first section, a general introduction, the motivation for the study, and a literature review background are provided. In the second part, methodological approaches used to evaluate startup teams are identified, presented, and described. The following section presents the main results described in the paper. Firstly, this involves structuring the parameters for evaluating a startup team and determining the feasibility of obtaining numerical estimates for each. Secondly, this is a structured multi-criteria computer model for such evaluation built in MATLAB. Also, numerical examples of calculations are given. Finally, the fourth and last section of the manuscript discusses the directions for the next investigation, additional research perspectives, theoretical contributions, practical implications, and the limitations of the developed approach and the model.

2 Methodology

2.1 Research subsequences

The structure of the work on the article reflects the tasks set and is presented in Figure 1. It presents an overview of the methodology developed in this study, in the form of a workflow diagram. The diagram outlines four sequential phases, each comprising distinct functions or steps.

The subsequent sub-sections provide a definition and concise explanation of the specific modeling techniques designed and applied within the scope of this research.

2.2 Fuzzy approaches for evaluation of startup teams

Recently, fuzzy methods have been increasingly used to evaluate startup teams, as demonstrated by Kumar et al. (2023), Lin et al. (2021), and Bandurin (2023). Fuzzy logic enables the analysis of non-formalizable, subjective, and qualitative characteristics such as motivation, synergy, leadership qualities, and team compatibility. Several key fuzzy approaches used for team evaluation can be identified.

One of the most common approaches is Fuzzy Multi-Criteria Decision Making, which extends classical methods (AHP, TOPSIS, ELECTRE) by incorporating fuzzy values, as described by Bölükbaş et al. (2025), Puzović et al. (2023), and Kyrylych & Povstenko (2023). These methods are suitable when expert judgments are expressed in linguistic rather than numerical form.

Fuzzy AHP is widely used to determine the weights of team evaluation criteria based on linguistic expert assessments such as “high experience,” “moderate involvement,” or “low conflict.” Triangular or trapezoidal fuzzy numbers are typically used in the models. FAHP effectively captures uncertainty and subjectivity in expert opinions, although it requires careful specification of membership functions, as shown by Salehzadeh & Ziaeian (2024) and Alharairi et al. (2025).

Another method is Fuzzy TOPSIS, which evaluates startup teams based on their closeness to fuzzy “ideal” and “worst” solutions. This approach, argued by Afful-Dadzie & Afful-Dadzie (2016), incorporates fuzzy assessments (e.g., “moderate coordination” or “high flexibility”) and scores teams on criteria such as reliability, communication, experience, and motivation.

Fuzzy Rule-Based Systems represent a different class of approaches. They rely on expert-defined IF–THEN rules, such as IF “experience” is high AND “coherence” is medium THEN “team quality” is high. Its components include a rule base, membership functions, and an inference engine, as shown in Dogan & Avvad (2025) and Mikulić et al. (2021). These systems are applicable for simulation

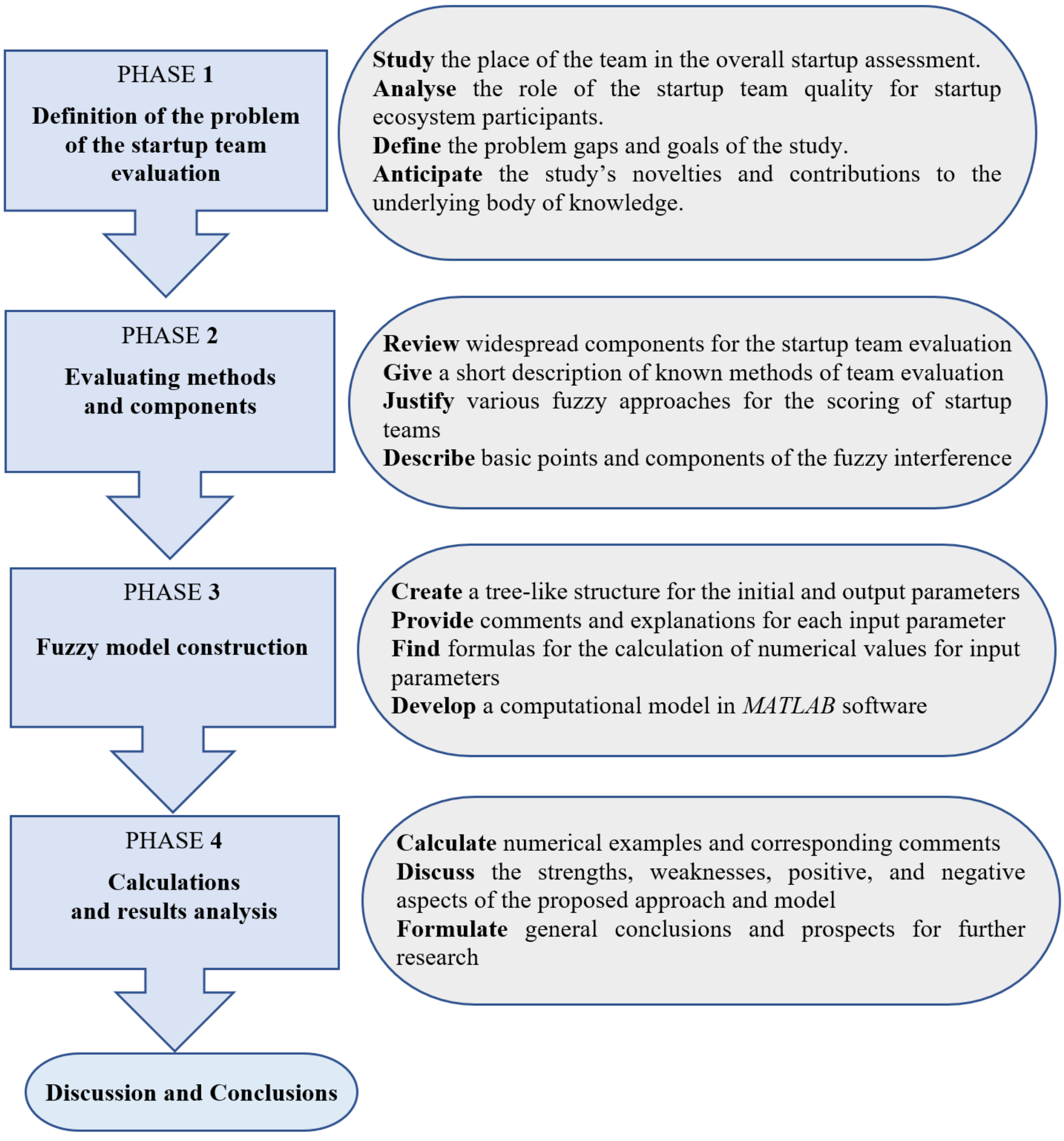

Figure 1: A workflow diagram for the research methodology used in the paper

Source: Composed by the authors

modeling and automated decision-making within acceleration platforms, venture CRM tools, etc.

Fuzzy Cognitive Maps (FCM) constitute another widely used methodology, as confirmed by Tchupo et al. (2020). FCMs enable modeling causal relationships among team-related factors, such as motivation, leadership, experience, involvement, and charisma, and how they influence one another and overall team effectiveness. In this method, team qualities are represented as nodes, while causal links between them are assigned fuzzy weights provided by experts. This approach enables the analysis of team dynamics and the potential for strengthening or degradation over time.

An extension of classical fuzzy is Type-2 Fuzzy Logic, which explicitly accounts for uncertainty in the membership functions themselves. This approach, according to Mittal et al. (2020), is relevant in situations where expert judgments are inconsistent or contradictory and the boundaries of concepts such as "team synergy" are difficult to define. Its practical application remains limited due to high computational complexity, and holds promise for startup analysis involving heterogeneous or conflicting data sources.

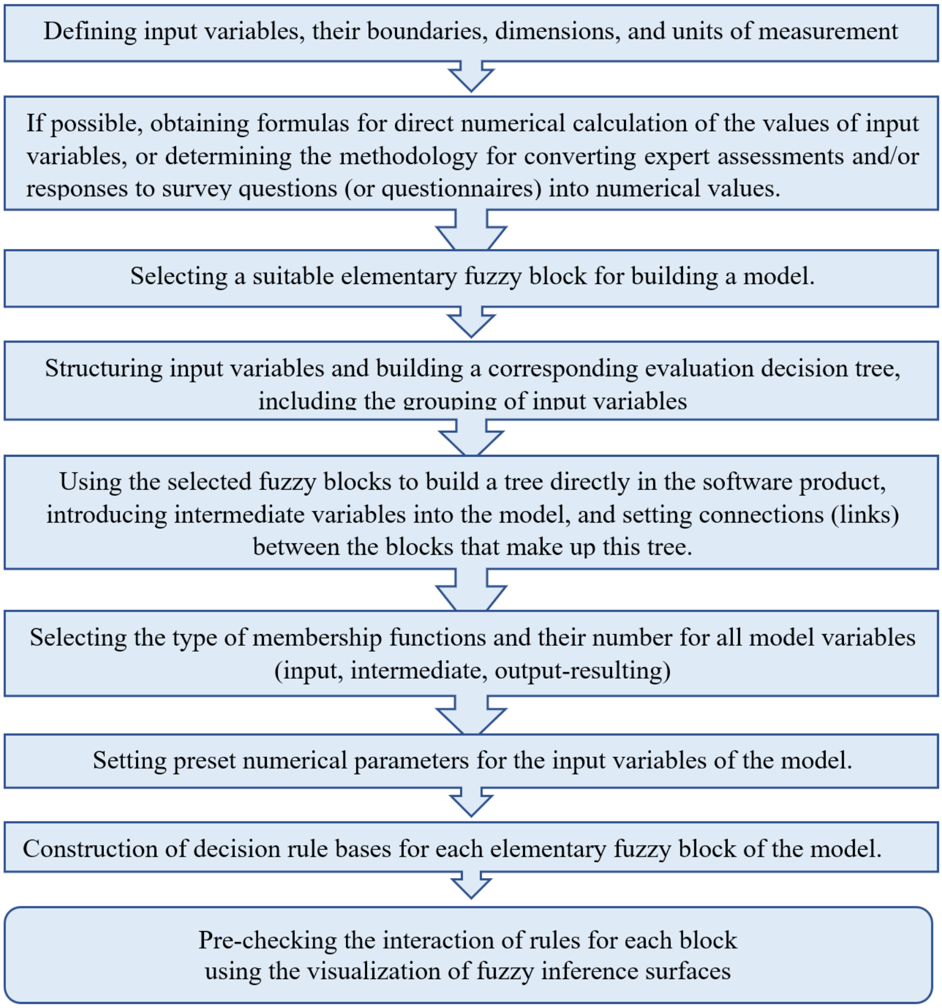

Figure 2: Model's development steps

Source: Composed by the authors

The Fuzzy Delphi Method combines the traditional Delphi technique with fuzzy aggregation mechanisms to achieve consensus among experts. As shown in Mohammadi & Shafiee (2021), Lianto (2023), and Alnoor et al. (2022), it is useful for evaluating startup teams using assessments from mentors, investors, or advisors, especially when formal performance indicators are unavailable.

Finally, fuzzy logic is often combined with fuzzy clustering, such as Fuzzy C-Means, to classify and group startup teams, which is illustrated in Dang et al. (2021) and Semerci et al. (2017). This allows teams to belong to multiple clusters with different degrees of membership, facilitating the identification of hybrid team types and associated strengths or risks. Overall, fuzzy-based approaches provide effective tools for evaluating startup teams under conditions of uncertainty, subjectivity, and limited data. Their main advantage lies in their ability to model human judgment and linguistic assessments, making them especially valuable in venture decision-making contexts.

2.3 An application of a fuzzy interference system for multi-criteria evaluation of startup teams

To address the challenge of multi-criteria evaluation for a startup team, given heterogeneous initial data and subjective expert assessments of their relative importance, we will employ a fuzzy-logic-based approach. The methodology for constructing such or similar systems for applied use is widely described in the literature, for example, in Varshney & Torra (2023), Furizal et al. (2024), and Saafor example, intchi (2024). However, it is also appropriate to briefly consider, describe, and comment on some key points related to our model.

Thus, we will use input linguistic variables (corresponding to certain initial characteristics used for evaluation) containing three membership functions. The membership functions will be triangular. Additionally, if it is necessary to specify an interval of the input variable within which the result remains constant, trapezoid functions should be used, as shown in Figure A1.

This figure illustrates the set, parameters, and type of membership functions for all input variables of the model, as well as potential changes to membership functions of input parameters when necessary to introduce greater fuzziness, softness, or a specific range of initial data that does not alter the result. The same applies to the membership functions of the intermediate and resulting variables. In the model, for all variables, input data, intermediate results, and final results (including their possible, maximum, and minimum values) are presented in the range of 0-100.

During construction, we will use two variants of elementary fuzzy blocks: those with 2 and 3 input variables. For each block, it is necessary to set the decision rules (rules) of fuzzy logical inference. Accordingly, the type of the rules themselves and their graphical interpretation are presented in Figure A2 (for two input variables) and Figure A3 (for three input variables, fragment).

The general development sequence for the fuzzy model is illustrated in Figure 2.

3 Results

3.1 Structure of multicriteria fuzzy logic-based inference systems for team evaluations

The tree for calculating the final overall assessment of a startup team, based on elementary initial criteria, is presented in Figure 3.

3.2 Explanation of parameters

As described earlier, the model we propose consists of seven main groups of elements, each with numerical values used to obtain the final, generalized assessment. Therefore, we will consider approaches to obtaining numerical assessments of the primary components of the startup team assessment model.

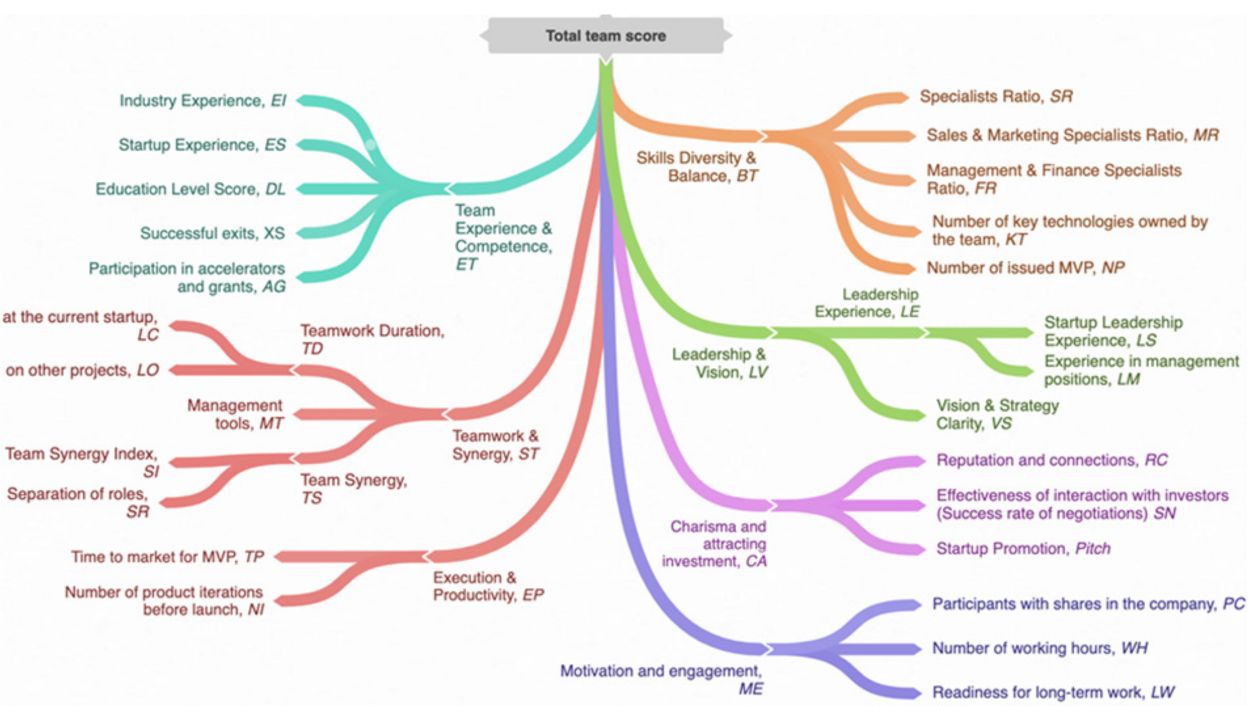

Figure 3: Input parameter composition tree for multi-criteria startup team evaluation

Source: Author's elaborations

Team Experience & Competence. Table B1 contains formulas for calculating the components included in its composition. When evaluating startups, team experience and competence are among the most critical factors influencing long-term success. Even with an innovative idea and a scalable business model, a startup's performance ultimately depends on the team's ability to execute strategy, adapt to changing conditions, and manage resources efficiently. Industry-specific experience allows founders to better understand market dynamics, customer needs, and competitive environments. Teams with strong domain knowledge tend to set realistic goals, develop well-founded strategies, and respond more effectively to market shifts.

The competence of founders and key team members directly affects the quality of managerial decisions, including strategic planning, operational execution, fundraising, and growth management. Empirical evidence from venture capital practice shows that startups led by experienced and skilled teams are more likely to reach market entry, secure additional funding rounds, and achieve sustainable financial results. In addition, teams with a proven track record of successful ventures inspire greater investor confidence, reducing perceived risk and signaling the ability to operate under uncertainty. Therefore, the Team Experience & Competence represents a core element of startup evaluation, significantly influencing investment attractiveness, scalability potential, and long-term resilience.

Skills Diversity & Balance. Table B2 lists the components of its composition. When evaluating startup potential, the diversity and balance of skills within the team are crucial in determining the likelihood of success. This criterion reflects the degree of functional complementarity among team members and directly affects the startup's ability to address the challenges of early-stage development.

Startups operate in environments characterized by high uncertainty and limited resources, requiring competence across multiple domains, including product development, technology, marketing, sales, legal, and finance. Teams with diverse skill sets can allocate responsibilities more effectively, reduce reliance on external support, and accelerate execution. In addition, a balanced skill composition improves decision-making by integrating different perspectives. Empirical studies indicate that functionally diverse teams demonstrate higher innovation levels and stronger market sustainability. Consequently, the Skills Diversity & Balance is a key element of startup evaluation, influencing problem-solving capacity, scalability, and long-term growth potential.

Teamwork & Synergy. This group includes the input variables shown in Table B3. When evaluating startups, this criterion deserves special attention, as it is a key indicator of organizational effectiveness and long-term sustainability under conditions of uncertainty and limited resources. Effective internal collaboration ensures coordinated actions, consistent decision-making, and efficient task execution. Early-stage startups operate in dynamic environments with tight deadlines, requiring strong communication, mutual trust, and collective adaptability. Teams with these qualities tend to manage stress more effectively, resolve conflicts faster, and maintain higher productivity.

Team synergy arises when collaborative results exceed the sum of individual contributions. This is achieved through clearly defined and complementary roles, respect for each member's expertise, and alignment around shared strategic goals. Synergy enhances creativity, supports innovative problem-solving, and accelerates product development and market entry. Additionally, strong team dynamics are viewed favorably by investors, as they reduce operational and managerial risks. Research indicates that poor teamwork, unresolved conflicts, and leadership disputes are common causes of startup failure, even when products are competitive. Therefore, the Teamwork & Synergy is an essential element of startup evaluation, reflecting a team's capacity for effective execution, adaptability, and sustainable growth in competitive environments.

Leadership & Vision. This criterion plays a central role in startup evaluation, as it reflects not only the team's strategic direction but also its ability to achieve long-term goals amid high uncertainty and a rapidly changing external environment. The included components are described in Table B4.

Effective leadership and a clear vision are key drivers of sustainable growth, organizational cohesion, and innovation in startups. Leadership strongly influences company culture, strategic decision-making, and resource allocation. In early development stages, an adaptable and goal-oriented leader is essential for motivating the team, managing crises, and navigating uncertainty. A clear and realistic vision supports strategic planning and market positioning by defining long-term objectives and aligning short-term actions with the chosen business model. Startups without a well-defined vision often face strategic inconsistency and inefficient resource use. Moreover, strong leadership and a coherent vision enhance trust among investors, partners, and customers. Empirical evidence shows that startups with capable leadership and strategic clarity are more likely to scale successfully, attract investment, and achieve sustainable growth. Consequently, the Leadership & Vision represents a core element of startup evaluation, combining strategic direction with managerial effectiveness and risk mitigation.

Execution & Productivity. Table B5 shows the components for this group. In evaluating startups, this criterion is crucial, as it reflects the team's ability to transform ideas into concrete actions and achieve operational goals under time and resource constraints. It captures not only strategic intent but also disciplined and systematic implementation typical of successful early-stage ventures. Key indicators include MVP time-to-market and the number of iterations before launch. A short MVP development cycle signals strong coordination, rapid decision-making, and a clear focus on essential market needs. At the same time, multiple pre-launch iterations demonstrate effective hypothesis testing, user feedback integration, and continuous improvement.

High productivity is evident in the team's ability to reach meaningful milestones despite uncertainty. This includes regular releases, adherence to timelines, timely resolution of blockers, and strategic adjustments based on external feedback. Empirical evidence shows that startups with consistent execution and operational efficiency are more likely to overcome early-stage challenges and secure follow-on funding. Thus, Execution & Productivity serve as strong indicators of scalability, adaptability, and long-term growth potential in competitive markets.

Charisma &Attracting Investment. It is described by the variables presented in Table B6. When evaluating a startup team, founders' charisma and ability to attract investment are crucial, especially in the early stages, when external funding often determines viability. Though largely behavioral and subjective, this criterion significantly influences pre-seed and seed-stage success. A charismatic founder can clearly convey an inspiring vision and effectively communicate the startup's value proposition to investors, customers, and partners. In competitive fundraising environments, qualities such as confidence, persuasiveness, and emotional intelligence often become decisive.

The ability to attract investment also reflects the team's social capital, including professional networks, experience with accelerators or venture funds, and the capacity to build trust-based, long-term relationships. This enhances the likelihood of securing initial funding, follow-on rounds, strategic partnerships, and market expansion. Empirical evidence shows that charismatic leaders drive higher team engagement, lower turnover, and greater loyalty from early adopters. Therefore, the Charisma & Ability to Attract Investment is a key indicator of entrepreneurial potential and the team's capacity to communicate the value of their innovation in high-risk, low-trust environments.

Motivation &Engagement. This group includes the variables listed in Table B7. For a startup team, motivation and engagement are key criteria for sustainable development. They reflect the team's readiness to overcome challenges and maintain focus, creativity, and productivity in the face of uncertainty and limited resources. High motivation underpins entrepreneurial persistence, enabling the team to endure failures, iterate quickly, and adapt to changing circumstances. Intrinsic motivation indicates personal commitment to the startup's mission and a drive to create value beyond profit.

Engagement is expressed through active participation in key processes and accountability for outcomes. Highly engaged teams demonstrate greater coherence, faster decision-making, greater flexibility, and greater resilience to stress, which helps achieve product-market fit more quickly. Ownership stakes, working hours, and long-term commitment further reinforce responsibility and dedication.

Investors often view energy, proactiveness, and focus as indicators of strong entrepreneurial potential. Conversely, low engagement, divided attention, or weak commitment may signal a high risk of early abandonment. Therefore, this criterion serves as a crucial measure of a team's internal strength, resilience, and ability to sustain effective work under pressure while continuously improving and adapting in a high-uncertainty environment.

3.3 Model creation in MATLAB

Based on the above-described input data and the tree representing the composition's structure, a corresponding model was built to provide an integrated assessment of the startup team's performance. It should be noted that MATLAB was used under the University of Tartu license, but this licensing requirement is not a limitation, since a completely identical model can be built in the same way using the freely available SCILAB software.

The model has 26 input variables (initial evaluation criteria) and 14 intermediate variables, distributed across 18 elementary fuzzy blocks (11 with 2 and 7 with 3 input variables). It is not practical to use more than three input variables for an elementary fuzzy block, since this dramatically increases the number of fuzzy decision rules that need to be specified in such a case.

Intermediate fuzzy blocks and their variables in the model are additional and are used to sequentially combine estimates (input variables) according to the decision tree structure (estimation). Accordingly, intermediate output variables serve as inputs for the next level of the model.

In general, if necessary, several output variables can be used to obtain a generalized, integrated estimate not only for all 26 input variables, but also for individual (interesting) groups of input data or their specific combinations.

For visual control of the correctness of the decision-making rules set for each elementary fuzzy block, fuzzy inference surfaces can be used. They demonstrate the dependence of the result on the input variables and should have a form similar to that shown in Figure 7, monotonic and smooth, without sharp jumps, dips, minima, or maxima.

As mentioned above, the model uses triangular membership functions and decision rules corresponding to the case "input parameter value is greater, result value is greater".

In cases where the situation (the dependence between input and output variables) is opposite for some input parameters ("input parameter is greater - result is less"), the model should be minimally reconfigured, changing only the designations for the linguistic terms of the corresponding input variable. In this case, all other components of the model, and, most importantly, the decision rules themselves, remain unchanged.

In the form presented, the model for all variables uses a 100-point scale. Therefore, if some variables have other dimensions, value boundaries, and units of measurement, there are two possible ways to adjust the model. The first option is to pre-match the numerical value of the input variable with the expert assessment, which is then used in the model. The second option is to fine-tune the model itself by replacing the numerical values of the expert version with the existing numerical values (boundaries and point characteristics of the membership functions) for the corresponding variable in the model.

In practice, it is possible that the values (or estimates) of some of the input parameters of the assessment are missing (or cannot be used for some reason). In this case, the calculation (without changing the model itself) can be performed using three options: pessimistic, average, or optimistic.

In the first option, the missing data are replaced by the minimum values for unknown (unused) input data; in the second, by average values; and in the third, by maximum values (worst-average-best approach). Also, if this is due and justified by the circumstances, it is possible to select different options for different startups, even when comparing them simultaneously.

The general view of the complete model in MATLAB is shown in Figure 4.

3.4 Results of numerical calculations

For example, consider applying this model to evaluate teams at four startups. The initial data and all calculation results for them are presented in Table 1. The fill colors in the table correspond to the colors of the tree parts shown earlier in Figure 3.

In the general case, the numerical calculations can include searching, determining, or preliminary formulaic calculation of the values of the initial data (input parameters for evaluation); preparing an Excel file with input data for exchanging information with MATLAB, calculations in the model directly in MATLAB, and loading the results back into the Excel file.

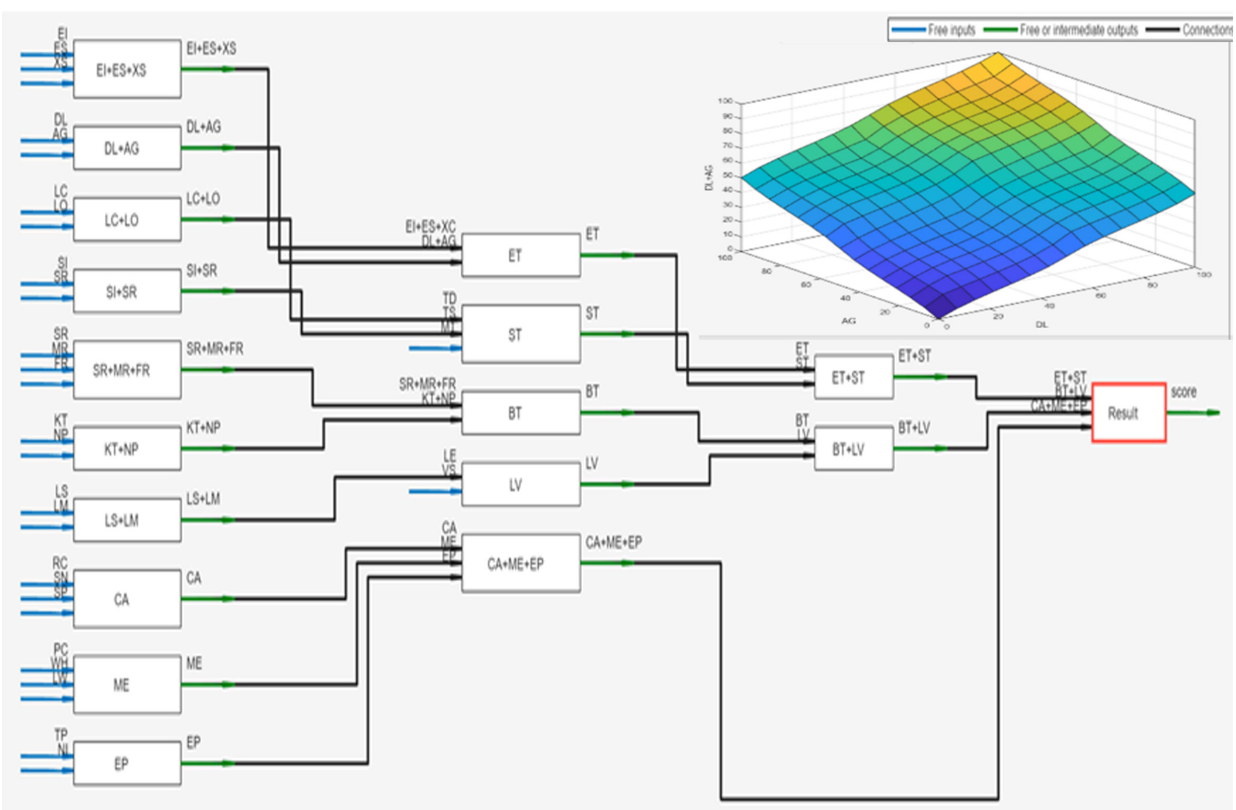

Figure 4: The full model in MATLAB and the control surface (top right) for the 2-input case

Source: Developed by the authors

Table 1: Input data, intermediate, and final results of calculations, case of experts

variable names		Startup1	Startup2	Startup3	Startup4
in the calculation tree	in the model				
Input variables					
Industry Experience	*EI*	85	60	70	35
Startup Experience	*ES*	80	55	65	30
Successful Exits	*XS*	70	40	30	10
Education Level Score	*DL*	75	65	80	50
Participation in Accelerators	*AG*	65	50	45	20
Time........in the current startup	*LC*	75	60	55	35
Time........on other projects	*LO*	65	55	60	30
Team Synergy Index	*SI*	80	65	60	40
Separation of roles	*SR*	85	70	65	45
Management tools	*MT*	75	60	55	35
Specialists Ratio	*SR*	80	65	75	55
Sales & Marketing Specialists Ratio	*MR*	75	60	40	25
Management & Finance Specialists Ratio	*FR*	70	55	45	30
Number of key technologies owned by the team	*KT*	85	65	90	50
Number of issued *MVP*s	*NP*	80	60	70	40
Startup Leadership Experience	*LS*	80	55	60	30
Experience in management positions	*LM*	85	65	55	35
Vision & Strategy Clarity	*VS*	90	70	65	45
Reputation and connections	*RC*	85	60	55	30
Effectiveness of interaction with investors	*SN*	80	55	50	25
Startup Promotion	*SP*	85	65	45	30
Participants with shares in the company	*PC*	75	70	65	50
Number of working hours	*WH*	80	75	85	70
Readiness for lõng-term work	*LW*	90	80	75	60
Time to market for *MVP*	*TP*	75	65	80	50
Number of product iterations before launch	*NI*	70	60	75	40
Intermediate results variables					
*EI+ES+X*S	*EI+ES+XS*	77	53	56	24
DL+AG	*DL+AG*	71	58	60	35
Team Experience & Competence	*ET*	74	58	61	29
SR+MR+FR	*SR+MR+FR*	71	60	60	30
KT+NP	*KT+NP*	80	70	65	40
Skills Diversity & Balance	*BT*	75	67	63	32
Teamwork Duration (*LC+LO*)	*TD*	74	64	51	37
Team Synergy (*SI+SR*)	*TS*	80	66	79	44
Teamwork & Synergy	*ST*	76	68	65	37
Leadership Experience *(LS+LM)*	*LE*	80	62	60	30

Table 1: Input data, intermediate, and final results of calculations, case of experts (continues)

variable names		Startup1	Startup2	Startup3	Startup4
in the calculation tree	in the model				
Input variables					
Leadership & Vision	*LV*	82	69	66	36
Charisma &Attracting Investment	*CA*	79	64	50	27
Motivation & Engagement	*ME*	79	75	74	62
ET+ST	*ET+ST*	74	65	66	28
BT+LV	*BT+LV*	78	71	69	33
Execution & Productivity	*EP*	73	66	76	43
CA+ME+EP	*CA+ME+EP*	76	71	67	44
Final result variable					
Total Team score	*SCORE*	76	70	68	34

Source: Calculated by the authors

This table presents the results of the preliminary expert assessment of all input parameters on a 100-point scale. Individual numerical estimates can also be used with minimal adaptation of the corresponding elementary fuzzy blocks in the model. While the basic, initial model assumes that each input parameter is assessed by experts on a 100-point scale, the table also presents possible other units of measurement for individual parameters. The corresponding, more precise fine-tuning of the model is carried out during the review and preliminary preparation of specific input data, taking into account the task's specifics and the overall content of the corresponding database. In the absence of data for any parameter, the worst-average-best approach can be used. In this case, the missing values in the input parameters are replaced during calculations with the minimum, average, or maximum value, respectively.

A preliminary look at the results shows that, both for the overall integrated assessment and for the individual evaluation components and their groups, it is possible, if necessary, to conduct a more in-depth analysis of specific aspects of a startup team. Overall, it is worth noting that Startup1 represents the strongest and most experienced team among those considered and demonstrates relatively high investment attractiveness. Startup2 appears to be a balanced, average, and "typical" startup. Startup3 is technically strong; however, it performs comparatively weakly in business development, leadership, and investment-related areas. Finally, Startup4 represents an early-stage startup, a less mature project associated with relatively high and sensitive risks.

4 Discussion

The results in Table 1 demonstrate significant differences in the structure and overall strength of the startup teams. Startup 1 demonstrates consistently high values across most input and intermediate variables, resulting in the highest integrated overall team score. Startups 2 and 3 form the middle group, with relatively balanced profiles, while Startup 2 shows stronger motivation and engagement indicators. However, Startup 3 demonstrates stronger execution and performance indicators, including mastery of technology and iteration dynamics. Startup 4 demonstrates the lowest values across both input and aggregate indicators, resulting in a significantly lower overall team score. Overall, the comparison shows that high scores on intermediate dimensions such as leadership, skill balance, and teamwork are associated with higher integrated team scores.

A more detailed analysis reveals that Startup 1 demonstrates particularly high scores in leadership, strategic vision, team experience, and skill diversity. Startup 2 has a relatively balanced team profile, highlighting motivation and engagement, as well as teamwork and leadership, resulting in a fairly good overall score. Startup 3 has strengths primarily in execution and performance, including mastery of key technologies, work intensity, and product iteration dynamics, while leadership and external engagement exhibit more moderate values, resulting in an intermediate overall score. Finally, Startup 4 demonstrates low values across most input and aggregate metrics, including experience, leadership, and synergy, resulting in a significantly lower overall team score within this group.

The proposed methodology and model for evaluating startup teams based on a combination of the above indicators are highly useful for analyzing their development potential. In the early stages, the team represents a key source of human capital and largely determines a startup's ability to formulate and implement strategy, adapt to environmental changes, and navigate highly uncertain environments. Characteristics such as industry and entrepreneurial experience, leadership qualities, balance of competencies, motivation, and work intensity are closely linked to the quality of decision-making, the speed of product development, and the efficiency of resource utilization.

From a practical perspective, an integrated team assessment enables us to identify differences among startups in terms of investment attractiveness and long-term sustainability. Higher values for the aggregate indicators are generally associated with a greater likelihood of attracting external financing, as strong teams reduce the risks related to market and product uncertainty for investors. Furthermore, teams characterized by strong synergy, clear role assignments, and high engagement tend to progress more quickly through the MVP development, hypothesis testing, and scaling stages, thereby accelerating time-to-market and increasing the project's competitiveness.

Thus, using a structured team assessment model not only ensures a more objective and comparable assessment of startups but also serves as a basis for management and investment decisions. The results of such an assessment can be used to identify the team's strengths and weaknesses, adjust development strategies, and inform decisions regarding support, acceleration, or funding of startup projects. These results can be used both by teams for self-assessment and by other participants in the entrepreneurial ecosystem for evaluating competitors and startups.

Considering the presented model, it is worth noting its methodological novelty. Despite a significant number of publications devoted to evaluating startups, the methods, approaches, and practical tools for multi-criteria evaluation of the quality and level of startup teams proposed in them require further development. In this context, the use of the proposed approaches of fuzzy logic, the development of the corresponding model, and its computer implementation in specialized software are a strong methodological approach, and at the same time, a highly sought-after practical tool for the integral evaluation of the level and quality of startup teams, necessary for all participants (components) of the startup community.

Table 2: Model advantages and improvement directions

Advantages of the approach and the model	Directions of model development
Direct and relatively simple, without intermediate transformations, normalizations, etc., combination in calculations of input data presented in different units of measurement and different scales, with different min-max boundaries	Search, definition, construction, use of mathematical formulas, and elementary subparameters for more accurate numerical calculation of the values of the input parameters of the model
Taking into account the inaccuracy and underdetermination of decision-making rules (construction of integral assessments) by using the appropriate type of membership functions, the type and combination of individual rules from the rule base	Study of the structure and possibilities of reducing the number of decision-making rules with a large number of input variables of the elementary fuzzy block of the model, and without noticeable deterioration of the results (small deviation of the results in the case of reducing the number of rules compared to the standard set of rules)
Availability of opportunities and tools for adapting the initial, general model, taking into account the scope of the startup's activity, its stage, existing specific requirements, and conditions for evaluating the team.	Research on the dependence of results on the forms and types of membership functions in elementary fuzzy blocks of the model of different levels, the possibility of using additional weight parameters both in the combination of input variables and for a set of decision-making rules
Obtaining the desired, calculated, resulting numerical generalized estimate for any type, composition, and combination of input data.	Construction of a methodology for presenting input data in case of their incompleteness (absence, unknown, weak certainty of some) under various scenarios (pessimistic, average, optimistic) regarding missing values
Use of valid and reliable numerical calculation algorithms provided by a specialized, strong theory-based, and verified software	Mastering the capabilities of the software product itself for checking the consistency of rules and the validity of the parameters of linguistic terms of membership functions
Possibility of fragmentation and/or composition of fuzzy models for cases of different amounts of initial data (parameters) and required output results	Developing approaches to model management to adapt it to a wide range of cases – disabling certain variables or branches of the model, excluding some rules, and adding additional output variables
Communicability with *Excel* for exchanging input/output data and scalability of the fuzzy model by creating an installable and then executable application independent of the creation environment (*MATLAB*)	Study of the possibility of creating user interfaces for the model, both directly in *MATLAB* and in Excel, as an add-on; determination of the features and possibilities of creating installations and running applications for computers without *MATLAB*

Source: Developed by the authors

The developed model enables the generation of an integrated assessment of a startup team and tracking its dynamics as the initial data changes. Firstly, it enables continuous team monitoring, which is important for analyzing the impact of actual changes in certain parameters over time. Secondly, similar to simulation modeling approaches, it allows numerical and computational experiments to determine the necessary changes in certain parameters to achieve the desired level for the team as a whole or for its aggregated components in its overall assessment. Furthermore, the relative importance of selected factors in calculating the overall assessment can vary, given the practical realities of assessing startup teams at different stages, industries, and other specific conditions.

4.1 Theoretical Contributions

The theoretical component of the presented model involves systematizing the elementary components of the initial (input) parameters (criteria) for evaluating a startup team, structuring them, and generalizing them by creating a common tree to obtain an integrated assessment.

The possibilities of calculating numerical assessments for initial assessment parameters are also generalized; the corresponding formulas are proposed, along with their explanations and descriptions.

The methodology for creating elements and the structure of a fuzzy model for the practical calculation of an integral assessment are also proposed. The application of the model's components, as well as the steps and stages of its computer implementation, are substantiated and described.

Table 2 presents the main advantages of the described model, as well as the prospects for its further development and directions for improvement.

4.2 Implications for Practice

The proposed methodology and the developed computer model provide valuable information for various participants in the startup ecosystem. For investors, it allows for a more objective assessment of team potential, identification of strengths and weaknesses, and prediction of the startup's ability to adapt to market changes and manage risks, thereby increasing the likelihood of a successful investment. For accelerators and business incubators, the model helps rank applications, select teams with the highest potential for accelerated growth and effective resource use, and monitor progress during the acceleration process. For startup teams, the model provides structured feedback, highlights areas for improvement, and enables adjustments to team formation strategies, role distribution, and competency development. Thus, the tool contributes to increased transparency, objectivity, and systematic decision-making, enhancing the chances of successful project development.

4.3 Limitations

Table 3 highlights the model's existing shortcomings and describes the potential to eliminate and overcome them.

Table 3: Model disadvantages and ways to overcome them

Model's shortcomings and weaknesses	Ways to overcome limitations
Complexity and privacy issues in obtaining data on real startup teams, as well as extreme boundary values of input parameters to fine-tune the model for specific conditions	Use of open databases, accessible state and other public statistical information, materials from startup incubators, accelerators, and other components of the startup environment
A significant number of input parameters and other data, which are required for preliminary calculations of their values using formulas	Creation of flexible fuzzy evaluation models, with the possibility of partial disabling of parameters, variable decision rules, and flexible structure
The need for precise and adequate adjustment of decision-making rules	Using expert assessments and fine-tuning of models using internal tools of the development environment for fuzzy inference systems
Necessity of use of licensed software (*MATLAB*, *Excel*)	Development of a model similar in functionality and appearance using free software (*SciLab*, *OpenOffice, R* language)
The impossibility of carrying out calculations for end users who do not have specialized programs in the environment in which the computer model was developed	Creation of independent applications in the form of executable files installed on the user's computer, and not requiring, in addition to *Windows*, any other additional software

Source: Developed by the authors

4.4 Directions of Next Investigation and Further Research Perspective

Further development of the proposed model and methodological approach may include several directions.

This is, first and foremost, the clarification of the initial, elementary, and individual criteria for evaluating startup teams. In this case, both unification and detailing of these criteria are possible.

Another important issue here is the possibilities (and corresponding formulas) for obtaining numerical values of input parameter assessments. On the other hand, if expert assessments are based on indirect information or survey responses, then the digitalization of such assessments also requires appropriate methods and their practical testing.

Another important point is adapting the general, comprehensive decision tree to various practical situations, such as the actual assessment of a specific startup, while accounting for its maturity level, line of business, and other specific conditions.

Fine, accurate adjustment of the decision tree should enable the control of the importance of certain components, i.e., utilize their weights, and also easily combine numerical, expert linguistic, and binary assessments without internal restructuring of the model, simply by managing additional external parameters of its adjustment.

Special attention should be paid to clarifying the type of membership functions, which requires accumulating a base of numerical calculations for various startup teams and subsequently analyzing the results.

The model can also be supplemented with additional output variables that specify partial assessments of the startup team in the desired context, with the corresponding subset of input data. In this case, some decision-making rules can also change; that is, new rules can be added to the new set of rules and/or some existing rules can be removed from the initial set.

5 Conclusion

It should be noted that the empirical basis for developing the model structure, selecting input parameters, and configuring the fuzzy inference rules was derived from aggregated data from more than 60 startups that participated in the CDL Estonia program, as well as expert assessments from investors and mentors involved in this accelerator.

The calculation examples presented in the article are intended to demonstrate the process of model construction and operation, the logic of indicator aggregation, and the interpretation of integrated results. The use of aggregated data for the analyzed startups ensures the protection of confidential information related to real teams, which is a standard practice in studies focused on human capital assessment and venture evaluation.

At the same time, the proposed model can be directly applied in real-world decision-making processes, such as preliminary startup screening by investors and accelerators, ranking applications for acceleration and incubation programs, and internal team diagnostics to identify areas for development. Thus, the article provides a methodological foundation for the practical application of the model, while future research may focus on its validation using specific real-world cases and on expanding the empirical base.

The startups used in the calculation examples are based on real projects that participated in the CDL Estonia program. Approximately 80% of the initial characteristics and team structures correspond to real startup data, while certain parameters were partially aggregated, adjusted, or modified to comply with confidentiality requirements or due to the absence of complete information for some indicators. This approach preserves the realism and practical relevance of the illustrative examples without violating ethical or legal constraints on using data on specific teams.

Thus, moving on to the final conclusions, the following can be emphasized. Evaluating the startup team is a highly relevant and in-demand task for all participants, components, and structures within the startup community and the broader entrepreneurial ecosystem. The complexity of its solution stems from poorly defined, insufficiently formalized input data and strong subjectivity in evaluation, which can be overcome by using fuzzy-logic-based approaches.

The article proposes a methodology that includes predefined values for a set of individual evaluation parameters, their composition into a decision tree with corresponding rules, and the calculation of a general integral numerical assessment using a fuzzy inference system. This approach is implemented in a MATLAB computational model.

The calculations performed demonstrated the model's potential practical application, as well as the directions for its development, refinement, and adaptation to various practical tasks of evaluating startup teams. The described methodological approach and its model implementation are powerful tools, useful both for practical application and the practical assessment of startup teams in the context of making various management, financial, and other decisions. At the same time, they provide opportunities to develop and study scientific problems related to startup assessment, both in general and in specific conditions and applications.

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Razvoj metodologije, temelječe na mehki logiki, za reševanje problema ocenjevanja startup ekipe v pogojih negotovosti

Namen/cilj: Namen članka je razviti metodologijo za ocenjevanje startup ekip ter oblikovati ustrezen računalniški model, ki temelji na večkriterijski analizi in odločanju z uporabo mehke logike. Posebna pozornost je namenjena opredelitvi tako kvalitativnih kot kvantitativnih značilnosti ekipe ter pridobitvi posplošene integralne ocene startup ekipe v pogojih negotovosti.
Zasnova/metodologija/pristop: Predlagana je integrirana metoda ocenjevanja, ki združuje načela pristopa mehkih množic in ekspertnega vrednotenja ter je implementirana kot sistem mehke sklepanja v okolju MATLAB. Razviti model uporablja različne začetne značilnosti startup ekipe kot vhodne parametre. V ta namen so bile identificirane, opisane in uporabljene formule za izračun vrednosti teh ocenjevalnih parametrov. Opredeljen je bil nabor jezikovnih spremenljivk ter sistem pravil za obdelavo mehkih podatkov. Empirično osnovo raziskave predstavljajo podatki iz literature, ocene strokovnjakov in investitorjev ter študije primerov dejanskih startup projektov.
Ugotovitve: Rezultati kažejo, da predlagani pristop omogoča razmeroma objektivno in celovito oceno kakovosti startup ekipe, saj upošteva več ocenjevalnih meril, njihove medsebojne povezanosti ter kombinacijo kvalitativnih in kvantitativnih vhodnih podatkov v razmerah izrazite negotovosti. Metodologija zagotavlja objektivnost in ponovljivost ocenjevanja, zaradi česar predstavlja uporabno orodje za podporo odločanju v različnih situacijah in za različne udeležence v startup okolju.
Raziskovalne implikacije/omejitve: Raziskavo omejuje omejena razpoložljivost podatkov o dejanskih startup ekipah za preverjanje modela, kar pušča precej prostora za izboljšave, ter potreba po nadaljnji empirični utemeljitvi in prilagoditvi celotnega mehko-logičnega modela, vključno s formulami vhodnih parametrov, jezikovnimi spremenljivkami in pravili odločanja na podlagi strokovnih mnenj. Možna nadaljnja raziskovalna področja vključujejo prilagoditev metode različnim fazam razvoja startupov, upoštevanje področja delovanja, velikosti in drugih specifičnih značilnosti ter natančnejšo prilagoditev modela v različnih praktičnih primerih.
Izvirnost/vrednost/prispevek: Izvirnost članka se kaže v integraciji mehke logike in večkriterijske analize za ocenjevanje človeškega dejavnika v startupih. Pomemben prispevek predstavlja razvoj praktično usmerjenega orodja, ki povečuje natančnost in zanesljivost analize ekip, kar je bistvenega pomena za startupe, poslovne angele, sklade tveganega kapitala, pospeševalnike ter druge deležnike v startup skupnosti.

Ključne besede: *Ocenjevanje startup ekip, Metodologija mehke ocene, Model točkovanja ekip*

Appendix A

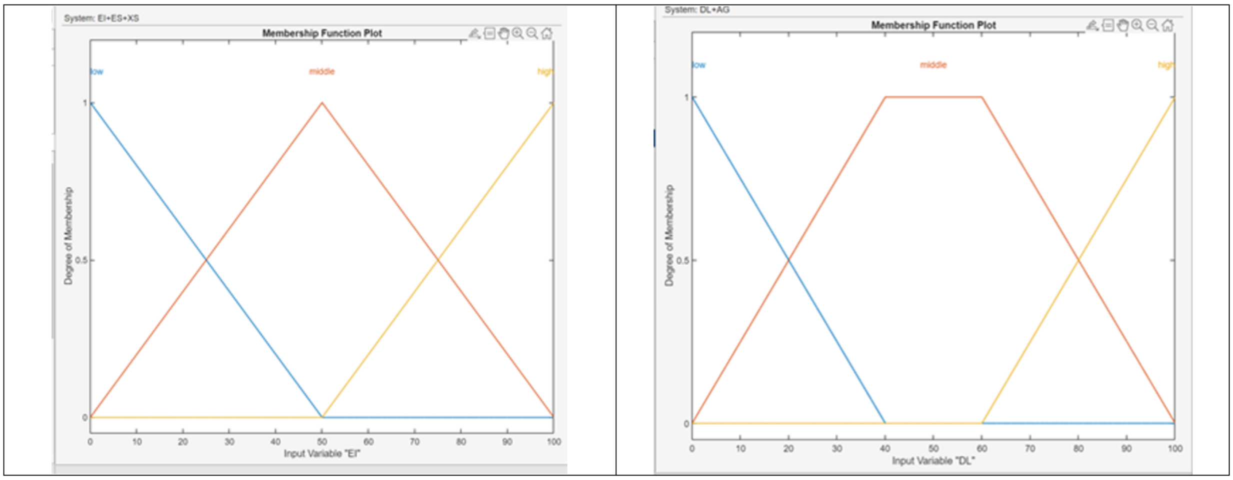

Figure 5: Membership functions: triangular (left) and trapezoid (right)

Source: Developed by the authors

Number of rules: 9 View in Rule Editor

	Rule
1	If (DL is low) and (AG is small) then (DL+AG is 2) (1)
2	If (DL is middle) and (AG is small) then (DL+AG is 3) (1)
3	If (DL is high) and (AG is small) then (DL+AG is 4) (1)
4	If (DL is low) and (AG is normal) then (DL+AG is 3) (1)
5	If (DL is middle) and (AG is normal) then (DL+AG is 4) (1)
6	If (DL is high) and (AG is normal) then (DL+AG is 5) (1)
7	If (DL is low) and (AG is big) then (DL+AG is 4) (1)
8	If (DL is middle) and (AG is big) then (DL+AG is 5) (1)
9	If (DL is high) and (AG is big) then (DL+AG is 6) (1)

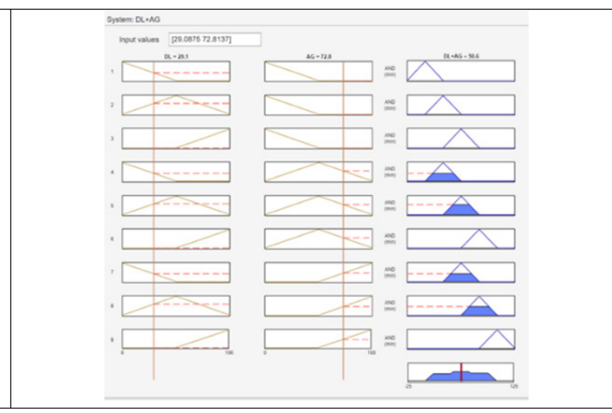

Figure 6: Decision rules set for the case of 2 input variables, and graphical interpretation of the interaction of decision-making rules and results

Source: Developed by the authors

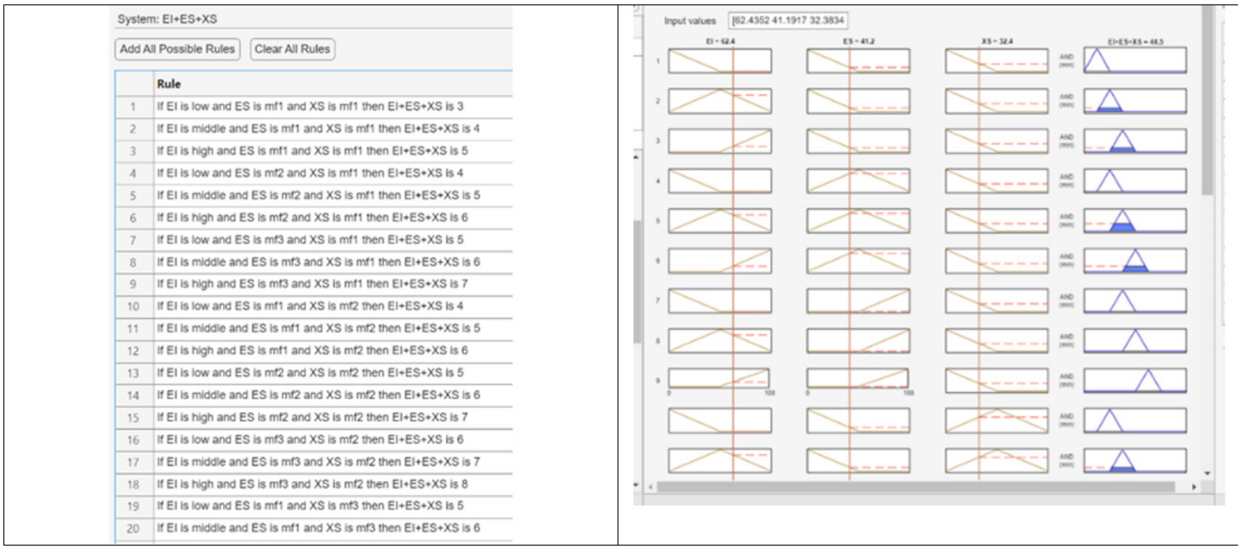

Figure 7: Decision rules set for the case of 3 input variables, and graphical interpretation of the interaction of decision-making rules and results

Source: Developed by the authors

Appendix B

Table 4: Calculations for the Team Experience & Competence group

Industry Experience, (E_i)	*Evaluation of Individual Team Member Experience:* $E_{relevant}$ — Experience in the target industry (years) E_{total} — Total work experience (years) E_{tech} — Experience in technological development (years) $E_{business}$ — Experience in business and management (years) $E_{startup}$ — Experience working in startups $Y_i = w_1 E_{\text{relevant}} + w_2 E_{\text{tech}} + w_3 E_{\text{business}} + w_4 E_{\text{startup}}$	*Team Experience Evaluation*: Description: The average number of years team members have worked in the target industry. $E_i = \frac{\sum_{i=1}^{N} Y_i}{N}$ where: Y_i - experience of the i-th team member. N - total number of team members. Unit of measurement: years.
Startup Experience, (S_e)	$S_{founder}$ — Number of startups founded by one member S_{team} — Number of startups where he worked S_{failed} — Number of unsuccessful startups (estimated as experience) S_{scaled} — Number of projects that achieved scalability $S_i = w_1 S_{\text{founder}} + w_2 S_{\text{team}} + w_3 S_{\text{scaled}} - w_4 S_{\text{failed}}$	*Startup experience:* Description: Average number of startups where team members worked. $S_e = \frac{\sum_{i=1}^{N} S_i}{N}$ where: S_i - number of startups where the i-th member worked. Unit of measurement: number of startups.
Education Level Score, (D_l)	D_{degree} – Level of education of one participant (gymnasium = 1, bachelor = 2, master = 3, PhD = 4, prof. = 5) D_{tech} - Education in the technical field (technical school = 1, bachelor = 2, master = 3, PhD = 4, prof. = 5) D_{business} - Education in business/management (bachelor = 2, master = 3, PhD = 4, prof. = 5) D_{self} - Courses, certifications (scale 1-4): number of relevant certificates - 1, 2, 3, 4 (4 or more) $D_i = w_1 D_{\text{degree}} + w_2 D_{\text{tech}} + w_3 D_{\text{business}} + w_4 D_{\text{self}}$	*Average level of education of participants:* $D_l = \frac{\sum_{i=1}^{N} D_i}{N}$ where: D_i - the level of education of the i-th team member. Unit of measurement: points.
Successful Exits, X_s	*Individual experience of each member of the team, X_i:* X_{IPO} - Number of companies that went public (IPO) X_{sold} - Number of startups sold $X_{\text{profitable}}$ - Number of profitable projects $X_i = w_1 X_{IPO} + w_2 X_{sold} + w_3 X_{profitable}$	*Successful exits*: $X_s = \frac{\sum_{i=1}^{N} X_i}{N}$ where: X_i - number of successful exits of the i-th participant. Units of measurement: number of successful exits.
Participation in Accelerators and Grants, (AG_p	*Quantity for each team member:* A_{top} - Participation in top accelerators A_{funding} - Grants and investments received $A_{\text{mentorship}}$ - Access to strong mentors Formula: $AG_i = w_1 A_{\text{top}} + w_2 A_{\text{funding}} + w_3 A_{\text{mentorship}}$	*Participation in accelerators and grants*: $AG_p = \frac{\sum_{i=1}^{N} AG_i}{N}$ where: AG_i – indicator of participation in accelerators and grants of the i-th team member. Units of measurement: number of activities.

Source: Developed by the authors

Table 5: Calculations for Skills Diversity & Balance group

Specialists Ratio (*SR*)	*Percentage of team members with relevant education:* $$SR = \frac{N_s}{N} \times 100\%$$ where: N_s - number of relevant professional specialists, N - total number of team members Units of measurement: %.
Sales & Marketing Specialists Ratio (*MR*)	$$MR = \frac{N_m}{N} \times 100\%$$ where: N_m - number of sales and marketing specialists. Units of measurement: %.
Management & Finance Specialists Ratio (*FR*)	*Percentage of team members with management, finance, and strategic planning experience:* $$FR = \frac{N_f}{N} \times 100\%$$ where: N_f - number of management and finance specialists, N - total number of team members. Units of measurement: %.
Number of key technologies owned by the team (*KT*)	*Units of measurement: pieces, how many technologies key employees know.*
Number of issued *MVPs*	*Number of issued MVPs (pieces):* the number of working prototypes created by the team earlier.

Source: Developed by the authors

Table 6: Calculations for the Teamwork & Synergy group

<table>
<tr><td rowspan="2">Teamwork Duration (TD)</td><td colspan="2">Length of time working together at the current startup ($L_{startup}$):
$$L_{\text{startup}} = \frac{\sum_{i=1}^{N} Ws_i}{N}$$
where:
Ws_i - number of years of joint work in the current startup for i-th member; Units of measurement: years.</td></tr>
<tr><td colspan="2">Experience of working together on other projects L_{past} :
$$L_{\text{past}} = \frac{\sum_{i=1}^{N} Wp_i}{N}$$
where:
Wp_i - number of years of joint work in other projects of the i-th member; Units of measurement: years.</td></tr>
<tr><td rowspan="2">Team Synergy (TS)</td><td>Team Synergy Index:
Considers the distribution of roles, shared values, culture, and level of interaction within the team.
Evaluated on a scale from 0 to 10.</td><td>$$T_{\square} = \frac{C + R + V + I}{4}$$
where:
C - communication level (from 0 to 10),
R - clarity of role distribution (from 0 to 10),
V - commonality of values (from 0 to 10),
I - level of integration into team (from 0 to 10).
Units of measurement: points (0-10).</td></tr>
<tr><td>Separation of roles:
Percentage of closed key positions (%).
For example, CEO, CTO, CMO, and CFO are 4 key positions.
If the number of them that are closed $-3 \rightarrow 75\%$.</td><td>$$RD = \frac{N_{cp}}{N} \times 100\%$$
N_{cp} − number of closed positions
N - total number of key positions</td></tr>
<tr><td>Management tools (MT)</td><td colspan="2">How effectively the team uses project management tools:
MT - using project management tools (0-10); Units of measurement: 0-10.</td></tr>
</table>

Source: Developed by the authors

Table 7: Calculations for the Leadership & Vision group

Leadership Experience (*LE*)	*Average Startup Leadership Experience:* $$SLE = \frac{\sum_{i=1}^{L} Ms_i}{L}$$ where: Ms_i - management experience of the i-th leader. L - number of leaders; Units of measurement: years.
	Average experience of team leaders in management positions (in corporate governance): $$CLE = \frac{\sum_{i=1}^{L} Mc_i}{L}$$ where: Mc_i - management experience of the i-th leader, L - number of leaders in the team. Units of measurement: years.
Vision & Strategy Clarity (*VS*)	*Clarity of the team's strategy (expert assessment):* $$VSC = \frac{V_S + M_S}{2}$$ where: V_S - clarity of vision (0-10), M_S - presence of a long-term mission (0-10). Units of measurement: points (0-10).

Source: Developed by the authors

Table 8: Calculations for the Execution & Productivity group

Time to market for *MVP*	*Time to market for MVP*: $$T_{\mathrm{MVP}} = T_{\mathrm{prototype}} + T_{\mathrm{launch}}$$ where: $T_{\mathrm{prototype}}$ - Creating a prototype T_{launch} - Launch into production Units of measurement: months.
Number of product iterations before launch	*Number of product iterations before Launch* Units of measurement: pcs.

Source: Developed by the authors

Table 9: Calculations for the Charisma &Attracting Investment group

Reputation and connections (*RC*)	$$RC = \frac{Reputation + Networking}{2}$$ where: *Reputation* – personal brand of the founders (0–10) *Networking* – having useful connections(0–10)
Effectiveness of interaction with investors	$$SN = \frac{IM}{A} \times 100\%$$ IM - Number of meetings with investors (pcs.) A - Number of signed agreements (pcs.) SN - Success rate of negotiations (%)
Startup Promotion	*Pitch* – presentations, website, social networks (0–10)

Source: Developed by the authors

Table 9: Calculations for the Motivation & Engagement group

Assessing Team Motivation (*ME*) M_{team}	E_{equity} - Percentage of members with shares in the company
	H_{work} - Average number of working hours per week; $\frac{H_{\mathrm{work}}}{80}$
	G - Willingness to work long term (scale 1-5); $\frac{G}{5}$

Source: Developed by the authors