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A FRAMEWORK FOR A VALUATION OF DIGITAL START-UPS USING ARTIFICIAL INTELLIGENCE AND FUZZY SETS

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Abstract

The purpose of this article is to present an innovative framework for assessing digital start-ups and smaller companies using a fuzzy set approach, considering the founder's expertise, product marketability, financial health, and social media presence. Four Czech digital startups were analyzed by both human experts and an artificial intelligence model. The methodology is based on using a fuzzy additive ratio assessment. Each start-up was evaluated on a five-point scale, with the results compared to Deloitte's FAST 50 rank. The AI and human evaluations differed, with humans placing more emphasis on the founder's experience and product appeal. As a practical contribution, the article suggests a valuation framework involving both human and AI expertise for interactive comparison and update. The article highlights the value of AI in start-up assessment, stressing the necessity of merging human and artificial intelligence in decision-making. To date of the publication, no study combining human expertise and artificial intelligence using fuzzy sets was found. Therefore, both methodology and results can be considered innovative and original.

Keywords

Digital start-ups; Artificial intelligence; Fuzzy sets; Company evaluation.

Introduction

The global economy has witnessed a significant transformation in the last several years, primarily driven by technological advancements and digitization. One of the key movers of this transformation is the advent of digital start-ups, which have profoundly affected the various dimensions of our economies, societies, and daily lives. Digital start-ups, inherently characterized by innovation, agility, and a high propensity for scalability, represent a potent force in driving economic growth. Digital start-ups serve as a key element in advancing digital transformation, affecting sectors as varied as healthcare, education, finance, and retail.

Financial investment is a crucial element of the success of digital startups. Start-ups with financial investment are more likely to survive and grow than startups without financial support. [1] However, the decision of a potential investor about an investment in a start-up is challenging. As most start-ups a newly created companies, traditional financial criteria do not provide a sufficient benchmark of a startup value and its future perspective [2], [3]. As can be seen in a literature review, investors use various criteria to decide whether they are going to invest in a digital start-up. Gathering information, evaluating it, and making decisions is a complicated and time-consuming process that requires know-how and knowledge in various fields. This article aims to formulate a framework that increases the efficiency of this process by using artificial intelligence (AI). The framework shall provide a good ability to explain the result to the decision-makers and allow the results to be compared with results provided by human experts (HE).

The framework uses a set of predefined criteria based on a literature review and it is primarily focused on publicly available data sources. The criteria are evaluated by AI and the results of a model are compared with valuation by HE. The evaluation framework uses fuzzy sets, which are aggregated. An individual evaluation of the importance of given criteria is included in the evaluation of the results. The article interprets the results of both approaches.

Several studies have been conducted on the investment criteria of investment firms (venture capital). Studies and analyses for various markets, conducted using different methodologies, arrive at different conclusions regarding decision-making criteria. The number of criteria and the strictness of their assessment vary across different markets. For instance, investors in the USA tend to consider more criteria than investors in Europe do.

Brooks et al. [4] evaluate the result of three start-up competitions and two experiments in the USA and discovered there was a statistically significant preference for attractive males among the winners. Widyanto et el. [5] identified 8 significant criteria using a survey sent to professional investors: long-term effort, risk valuation, market knowledge, leadership, previous success, market growth, acceptance of a product by a market, and availability of a prototype of a start-up's product. Crick & Crick [6] performed 20 interviews with business angels and evaluated the following criteria: foreign market orientation, team performance, approaches and data used for planning etc. Portmann & Mlambo [7] performed a survey among 56 investor subjects and identified the following criteria: the personality of a founder and a team (e.g., moral integrity, experience, ambition, and knowledge), acceptance of a product by market, and expected internal interest rate. Another survey focused on founders of start-ups was performed by Fichter et al. [8] who identified the personal characteristics of founders as a key criterion. Garkavenko et al. [9] have identified the following groups of criteria using a machine learning approach (2366 companies were included in the dataset): financial capital, human capital, product and technology, industry and market, social capital, and online environment. Keppler et al. [10] performed semi-structured interviews to conclude investors use industry-specific criteria, e.g., availability of clinical data for the medical industry. Miller et al. [11] performed a survey to find out investors are often more motivated by philanthropical reasons than by profit. Finally, Festel et al. [2] identified 5 groups of criteria (technological, product, organizational, implementational, and financial) using a literature review.

1 Research Objectives

The research presented in the article aims to focus on the following research objectives:

1. To evaluate and compare the performance of four Czech digital start-ups (FTMO, Knihobot, Apify Technologies, and DODO Czech) using human expertise and artificial intelligence, specifically ChatGPT-4.
2. To assess the utility and applicability of the fuzzy sets as a decision-making tool for ranking start-ups based on multiple criteria. The exact criteria are defined in the next section.
3. To explore the disparities between the FAST 50 ranking by Deloitte [25], human expert evaluation, and the AI-based evaluation and to identify the added value of both HE and AI.

4. To formulate a framework that can be used in the future research. The framework aims to enhance future valuation performance using research experience.

2 Research Methods

As can be seen in the literature review in the Introduction, various factors affect both success factors and investment decisions. However, it may be extremely challenging to evaluate some of the factors (e.g., personal characteristics of founders) using publicly available resources, such as financial databases, websites of companies, articles in highly relevant resources, or social media profiles of companies and their founders. As the presented framework aims to decrease the time required to evaluate a start-up, these criteria are not included in the framework. As a result, the following criteria were selected to be used: experience and human capital of the founder(s) of the start-up (C1), attraction of the product from the market view (C2), the financial situation of the company (C3) and presence and activity on social networks (C4).

A fuzzy set was used as a tool to evaluate each start-up based on the listed criteria. A fuzzy set is a concept in mathematics and computer science introduced by Zadeh [12] that provides a way of quantifying uncertainty and imprecision. Fuzzy sets are commonly used to evaluate and perform in uncertain conditions. [13]. It has already been used to evaluate technological start-ups by Arsenyan. [14] However, it is commonly used to evaluate several alternatives using predefined criteria in uncertain conditions. The example use cases of fuzzy sets are the selection of an energy source, [15], material in the automotive industry [16], the selection of a supplier [17], treatment of a patient with breast cancer [18], nuclear medicine imaging device [19], the most suitable product based on reviews of internet user [20], best locality of a logistical center [21], etc.

The key feature of the fuzzy set is it can provide a "common language" between the artificial intelligence and the human decision-maker. Both humans and artificial intelligence can evaluate the criteria using fuzzy sets, and the results can be compared and critically discussed. However, the evaluation of the criteria needs to be aggregated to get a final order of the alternatives.

Several methods can be used to create a final ranking order of the options. The authors focused on methods implemented in the pyFDM library created by Więckowski et al. [22] The Fuzzy Additive Ration was selected as the final assessment method. The application of the method with real-world examples can be found in articles [23], [24].

3 Results of the Research

As a first step of the practical part of the research, start-up companies for the evaluation were selected. After a preselection, 4 Czech digital start-ups from the FAST 50 rank were selected. [25] The companies included in the research are FTMO (A_1), Knihobot (A_2), Apify Technologies (A_3), and DODO Czech (A_4). The companies are listed in the FAST 50 rank by Deloitte, so the ranking of the companies is used as a benchmark [25].

The second step was evaluation of the start-ups by a board of four human professionals. The following evaluation criteria were used: experience and human capital of the founders, the attractiveness of the product from the market perspective, financial capital, social network presence and activity. The professionals were given a list of information about each company. The primary information taken into consideration is:

a) links to key documents about product descriptions
b) profiles of the founders on LinkedIn,

c) financial statements of the companies,
d) profiles of companies on social networks (Facebook, Twitter, and Instagram were primary sources as most of the companies are present there).

The professionals were free to use additional resources. The researchers used a 5-point scale to evaluate each start-up from the perspective of all criteria. The scale contained the following points: very low, low, average, high and very high. Additionally, each of the researchers using the same scale provided the weight of all criteria.

As a next step, the evaluation matrix was formed. Each entry in the matrix represents the rating of an alternative under a specific criterion. The ratings are represented as fuzzy triangular numbers. Tab. 1 displays the matrix.

Tab. 1: *The fuzzy decision matrix and fuzzy weights of four alternatives (HE)*

	C_1	C_2	C_3	C_4
A_1	(3.5, 5.5, 7.5)	(4.5, 6.5, 8.5)	(2.5, 4.5, 6.5)	(4, 6.0, 8.0)
A_2	(3.5, 5.5, 7.5)	(3.5, 5.5, 7.5)	(2.5, 4.5, 6.5)	(5, 7.0, 8.8)
A_3	(5, 7.0, 8.8)	(4.5, 6.5, 8.2)	(5, 7.0, 8.8)	(3, 5.0, 7.0)
A_4	(5.5, 7.5, 9.2)	(4.5, 6.5, 8.5)	(3.5, 5.5, 7.2)	(6.5, 8.5, 9.8)
Weights	(5.5, 7.5, 9.2)	(7.0, 9.0, 10.0)	(3.0, 5.0, 7.0)	(3.0, 5.0, 7.0)

Source: Own

As a further step, the normalized fuzzy matrix was calculated. As a next step, the data were normalized using formula (1)

$$\tilde{x}_{i,j} = \frac{x_{i,j}}{\sum_{i=0}^{m} x_{i,j}}, \tag{1}$$

where $x_{i,j}$ is the value of the ith value and the jth criterion, and m is the count of the alternatives [23], [24].

The normalized fuzzy matrix is shown in Tab. 2.

Tab. 2: *The normalized fuzzy decision matrix*

	C_1	C_2	C_3	C_4
A_1	(0.081, 0.152, 0.265)	(0.119, 0.215, 0.382)	(0.061, 0.134, 0.255)	(0.095, 0.173, 0.299)
A_2	(0.081, 0.152, 0.265)	(0.093, 0.182, 0.337)	(0.061, 0.134, 0.255)	(0.118, 0.201, 0.327)
A_3	(0.116, 0.193, 0.31)	(0.119, 0.215, 0.371)	(0.121, 0.209, 0.343)	(0.071, 0.144, 0.262)
A_4	(0.127, 0.207, 0.327)	(0.119, 0.215, 0.382)	(0.085, 0.164, 0.284)	(0.154, 0.245, 0.364)

Source: Own

Normalized fuzzy values were weighted by the given fuzzy weights of the criteria using formula (2)

$$\tilde{x}_{w(i,j)} = \tilde{x}_{i,j} * w_j , \tag{2}$$

where $\tilde{x}_{i,j}$ is the normalized value of the ith value and the jth criterion (calculated using formula (1)), and the w_j is the weight of the jth criterion [23], [24].

The weighted normalized fuzzy decision matrix can be seen in Tab. 3.

__Tab. 3:__ The weighted normalized fuzzy decision matrix

	C_1	C_2	C_3	C_4
A_1	(0.445, 1.138, 2.456)	(0.834, 1.934, 3.82)	(0.182, 0.672, 1.784)	(0.284, 0.863, 2.093)
A_2	(0.445, 1.138, 2.456)	(0.649, 1.636, 3.371)	(0.182, 0.672, 1.784)	(0.355, 1.007, 2.29)
A_3	(0.636, 1.448, 2.865)	(0.834, 1.934, 3.708)	(0.364, 1.045, 2.402)	(0.213, 0.719, 1.832)
A_4	(0.699, 1.552, 3.029)	(0.834, 1.934, 3.82)	(0.255, 0.821, 1.99)	(0.462, 1.223, 2.551)

Source: Own

Then, the overall performance index for the ith alternative was calculated using formula (3)

$$S_i = \sum_{i=1}^{n} \tilde{x}_{w(i,j)} \tag{3}$$

where the $\tilde{x}_{w(i,j)}$ is the weighted normalized fuzzy value of the ith value and the jth criterion (calculated using formula (2)).

The values are centralized using the center-of-area method (4).

$$\tilde{S}_i = \frac{1}{3}\left(S_{i,1} + S_{i,2} + S_{i,3}\right) \tag{4}$$

As a last step, the utility degree of the ith alternative was calculated using formula (5)

$$Q_i = \frac{\tilde{S}_i}{S_0} \tag{5}$$

where the $\tilde{S}_i$ is the centralized overall performance index of the ith alternative calculated using formula (4) and S_0 is the optimal utility function calculated as the best performance of the given alternatives.

The higher is the value of the utility degree, the better is the performance of the alternative. The calculations were performed using the Python library pyFDM [22] and following the description of the Fuzzy ARAS method in [23], [24]. The results can be found in Tab. 4. The ranking order of the start-ups is DODO Czech (A_4), Apify Technologies (A_3), FTMO (A_1), Knihobot (A_2).

__Tab. 4:__ The utility degree of the alternatives (HE)

A_1	0.7166
A_2	0.6939
A_3	0.7814
A_4	0.8322

Source: Own

The order of alternatives is different from the rank of the companies in the FAST 50 [25], which is as follows: FTMO (A_1), Knihobot (A_2), Apify Technologies (A_3), and DODO Czech (A_4). The results are further discussed in the next section.

As the last step of the research, all companies were evaluated by ChatGPT (version 4, May 24) [26]. As ChatGPT does not have a live connection to the internet, a set of information was provided for each criterion. For the C_1, the experience and education were gathered from the LinkedIn profiles of the founders of the start-ups. For C_2, the company product description from the official website was the key source. Additional data sources were articles published on the website of the company and paragraphs from the interview with the founders of the start-up. For the C_3, the last available 3 years were added to the prompt.

The financial statements were downloaded from the Orbis All Companies database [27]. To be more specific, the prompt contained key items from the profit and loss statements and key financial indicators, such as Return on Equity. The C_4 was evaluated using the ChatGPT instance available as a part of the Bing search engine. This instance has a more recent dataset available. It was able to evaluate the activity on social networks, including the number of reactions aggregated by months. The paid version of the tool was used, so the length of the prompt was limited to 4 thousand characters. The fuzzy decision matrix of ChatGPT is illustrated in Tab. 5.

Tab. 5: *The fuzzy decision matrix and fuzzy weights of four alternatives (AI)*

	C_1	C_2	C_3	C_4
A_1	(5, 7.0, 9.0)	(7, 9.0, 10.0)	(7, 9.0, 10.0)	(5, 7.0, 9.0)
A_2	(5, 7.0, 9.0)	(5, 7.0, 9.0)	(1, 3.0, 5.0)	(1, 3.0, 5.0)
A_3	(7, 9.0, 10.0)	(7, 9.0, 10.0)	(5, 7.0, 9.0)	(3, 5.0, 7.0)
A_4	(7, 9.0, 10.0)	(7, 9.0, 10.0)	(1, 3.0, 5.0)	(5, 7.0, 9.0)
Weights	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)	(5.0, 7.0, 9.0)	(5.0, 7.0, 9.0)

Source: Own processing of data generated by ChatGPT [26] as a result of author's prompts

Data in Tab. 6 were normalized using formula (1).

Tab. 6: *The normalized fuzzy decision matrix*

	C_1	C_2	C_3	C_4
A_1	(0.128, 0.226, 0.391)	(0.179, 0.281, 0.417)	(0.143, 0.205, 0.278])	(0.104, 0.167, 0.265)
A_2	(0.128, 0.226, 0.391)	(0.128, 0.219, 0.375)	(0.020, 0.068, 0.139)	(0.021, 0.071, 0.147)
A_3	(0.179, 0.290, 0.435)	(0.179, 0.281, 0.417)	(0.102, 0.159, 0.250)	(0.062, 0.119, 0.206)
A_4	(0.179, 0.290, 0.435)	(0.179, 0.281, 0.417)	(0.02 , 0.068, 0.139)	(0.104, 0.167, 0.265)

Source: Own

The weighted normalized fuzzy decision matrix in Tab. 7 was calculated using formula (2).

Tab. 7: *The weighted normalized fuzzy decision matrix*

	C_1	C_2	C_3	C_4
A_1	(0.897, 2.032, 3.913)	(1.256, 2.531, 4.167)	(0.714, 1.432, 2.500)	(0.521, 1.167, 2.382)
A_2	(0.897, 2.032, 3.913)	(0.897, 1.969, 3.750)	(0.102, 0.477, 1.250)	(0.104, 0.5, 1.324)
A_3	(1.256, 2.613, 4.348)	(1.256, 2.531, 4.167)	(0.510, 1.114, 2.250)	(0.312, 0.833, 1.853)
A_4	(1.256, 2.613, 4.348)	(1.256, 2.531, 4.167)	0.102, 0.477, 1.250)	(0.521, 1.167, 2.382)

Source: Own

The values of the performance utility index of each alternative can be seen in Tab. 8. The rank of alternatives is FTMO (A_1), Apify Technologies (A_3), DODO Czech (A_4), and Knihobot (A_2).

Tab. 8: *The utility degree of the alternatives (AI)*

A_1	0.8472
A_2	0.6204
A_3	0.8304
A_4	0.7953

Source: Authors' calculations in pyFDM [22]

The final comparison of all three rankings is provided in Tab. 9.

Tab. 9: *The comparison of ranking of the Companies*

Alternative	FAST 50	HE	AI	AI (C_1 - C_3)
FTMO (A_1)	1	3	1	2
Knihobot (A_2)	2	4	4	4
Apify Technologies (A_3)	3	2	2	1
DODO Czech (A_4)	4	1	3	3

Source: Authors' calculations in pyFDM [22]

4 Discussion of the Results

As clearly seen in Tab. 9, the rank of Deloitte is the rank created by AI. Both AI and HE placed Knihobot in 4th place. Knihobot was ranked by AI, especially in C_3 and C_4. Nonetheless, the activity of Knihobot on social media has recently increased, which explains the significance of the valuation of this criterion by HE and AI. The effect of the time-limited dataset of the AI model is present here. Withal, as can be seen in the last column of Tab. 4, Knihobot is evaluated as the last one even if C_4 is excluded. The rank of TMO and Apify Technologies is swapped if C_4 is excluded, yet there is no significant recent change in the activity of these start-ups, as the valuation of their activity by AI and HE is equal or very close. The second big difference is in the valuation of the financial capital of FTMO, which was significantly better valued by AI.

In the case of C_1 and C_2, AI was generally more positive in the case of all companies. As it does not directly affect rank, it might be useful to define the rank for these criteria in detail, so there is a better common understanding between both sides. Additionally, the results of FTMO were affected by very brief information on the LinkedIn profiles of both founders. The AI used its own database, which was clear from mentioning the former name of FTMO that was not provided in the prompt.

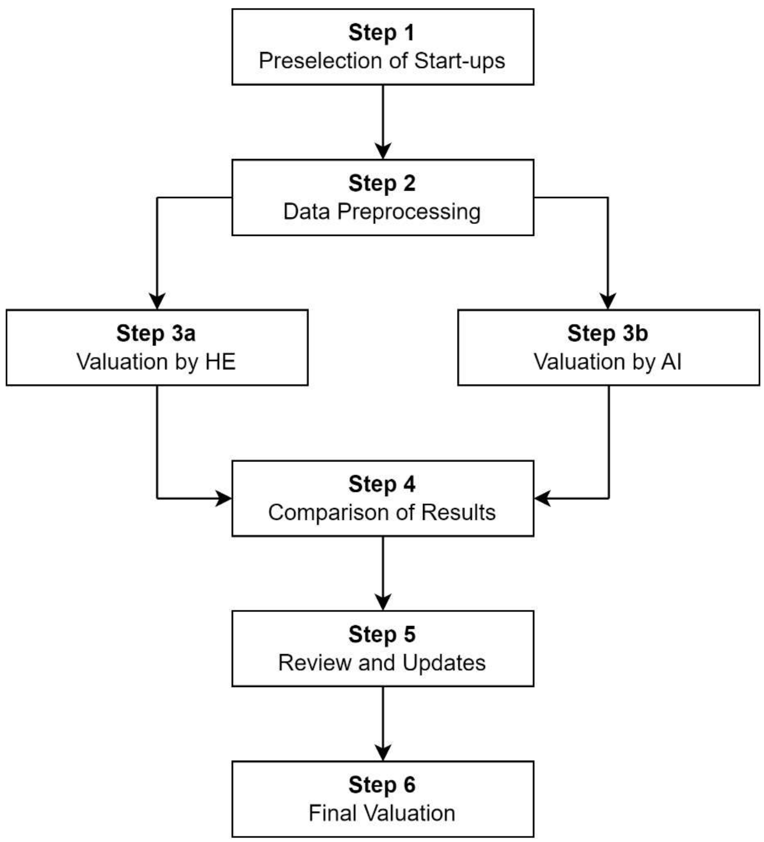
Regarding the weights, the HE gave relatively lower weights to C_3 and C_4. The valuation of AI has been recalculated using the weights provided by HE which results in swapping Apify Technologies and FTMO, i.e., the rank is equal to the rank without C4. It can be easily explained by the small margin between the first two companies and the significantly better performance of FTMO on social networks.

After the discussion of the results, the experience from the research process is used to define a valuation framework that can be used to solve similar tasks. The main conclusion is the research process was too linear, as the ranks were calculated separately and the reasoning of both HE and AI was not compared and critically reviewed. The ChatGPT provided a good and structured review of all valuations and it might bring additional facts and ideas useful for HE. As a result, a Comparison of Results and Review and Update steps were added to the framework. The complete description of the framework is given in the rest of this section. A graphical scheme is provided in Fig. 1.

The first step is the preselection of start-ups. As the valuation requires human work, it is recommended to preselect start-ups that should be evaluated. The start-ups can be preselected using a defined set of criteria, such as the location of start-ups, type of product, state of product, etc. After the preselection, key data and data sources are gathered, and data are processed. For example, the content of social network profiles can be downloaded using the APIs of social networks so the most recent content can be provided to the AI models. It is an open question whether AI should be involved in data preprocessing. It can provide valuable input for EA (e.g., clear explanation of highly technical concepts for HE without deep domain knowledge, extracting key points from long texts). On the other hand, the AI preprocessing might influence the valuation by HE towards AI. Nevertheless, both HE and AI should not be limited to the provided data and data sources.

The third step is divided into two parts: the valuation of companies by HE and AI. The valuation should be done independently, so the HE is not aware of valuation by AI and vice versa. The results are compared in the next step. The rating should be reviewed, especially when there is a significant difference between HE and AI. As AI provides reasoning for the results, it should be reviewed, and the argument of AI should be taken into consideration. AI model can also be asked for more detailed reasoning, and additional data gathering and research may be included if necessary. However, HE should be given the option to stand by their original decision. When all significant differences are settled, the valuation of HE should be updated. As a final step, the final rank of the start-up is provided.

It should be noted that the used valuation criteria are not a mandatory part of the valuation framework and they can be fully used with different sets of criteria. Potential users may leave out the fuzzy sets and use a different quantitative technique. However, the fuzzy sets have been shown as a good common tool for humans and AI.



Source: Own

Fig. 1: *Schema of the valuation framework*

New research should fully implement the framework, as it was not followed during the previous study based on the authors' experience.

Conclusion

In conclusion, the study presents a novel approach to start-up evaluation using both human expertise and artificial intelligence.

As the first research objective, the article aimed to evaluate and compare the performance of four Czech digital start-ups using human expertise and artificial intelligence. The start-ups were evaluated, and the results are described in Section 3. For evaluation, various criteria such as the founder's experience, product appeal, financial health, and social media presence were used. The evaluations were marked on a five-point scale, forming a fuzzy decision matrix, and the results were compared with Deloitte's FAST 50 rank [25].

As the second research objective, the utility and applicability of the fuzzy sets were to be evaluated and the result is shown in Section 3 and Section 4. It has been shown that fuzzy sets are an efficient tool for start-up evaluation, as they were proved to be easy to use by both human experts and generative AI models, and the results were easy to compare and evaluate.

The third research objective aimed to evaluate disparities between evaluation by human experts and artificial intelligence. These disparities were discussed in Section 4. The results demonstrated differences in evaluations by human experts and AI, pointing out the uniqueness of perspectives each side brings to the table. While human experts showed a tendency to value the founder's experience and product appeal, the AI model was observed to take a different evaluation approach, resulting in a divergence in rankings. This divergence prompted the study to suggest a dual evaluation framework that incorporates both human and AI inputs, enabling an iterative comparison, review, and update process. Such a process facilitates a more balanced and comprehensive assessment, harnessing the strengths of both AI and human evaluators. Moreover, the evaluation results indicated that AI was generally more optimistic about all companies in terms of founder experience and product attractiveness. This highlights the potential need for a detailed definition of these criteria to improve understanding between human experts and AI.

The last research objective was a formulation of a framework that can be used in future research. The framework was designed in the second part of Section 4. The framework was designed using the experiences from the research process. The process involves the preselection of start-ups, independent valuation by humans and AI, comparison and review of results, update of valuation, and finally, the provision of the start-up's rank. The framework allows for flexibility, as the used valuation criteria can be adapted based on specific needs.

In retrospect, although the research has provided insightful findings and proposed a useful framework, further research is recommended to fully implement and test this new framework. As this framework combines the strengths of human cognition and AI capabilities, it holds significant potential for robust start-up evaluation in the future. The implication is clear: in start-up evaluation, the harmonious blending of human expertise and AI can offer nuanced, insightful, and balanced perspectives.

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FRAMEWORK PRO OCEŇOVÁNÍ DIGITÁLNÍCH STARTUPŮ POMOCÍ UMĚLÉ INTELIGENCE A FUZZY MNOŽIN

Tento článek představuje inovativní framework pro hodnocení investic do digitálních startupů pomocí fuzzy množin. Framework zohledňuje odborné znalosti zakladatele, prodejnost produktu, finanční zdraví a přítomnost v sociálních médiích jako hodnotící kritéria. V rámci výzkumu byly analyzovány čtyři české digitální startupy, a to jak lidskými experty, tak s využitím umělé inteligence. Každý startup byl ohodnocen na pětibodové stupnici, přičemž výsledky byly porovnány s žebříčkem FAST 50 společnosti Deloitte. Hodnocení AI a lidských expertů se lišilo, přičemž lidé kladli větší důraz na zkušenosti zakladatele a atraktivitu produktu. Článek navrhuje framework, který interaktivně kombinuje hodnocení lidskými experty a umělou inteligencí.

EIN FRAMEWORK FÜR DIE BEWERTUNG DIGITALER START-UPS UNTER VERWENDUNG KÜNSTLICHER INTELLIGENZ UND FUZZY-SETS

In diesem Beitrag wird ein innovativer Rahmen für die Bewertung digitaler Start-ups und kleinerer Unternehmen unter Verwendung eines Fuzzy-Set-Ansatzes vorgestellt, der die Expertise des Gründers, die Marktfähigkeit des Produkts, die finanzielle Gesundheit und die Präsenz in den sozialen Medien berücksichtigt. Vier tschechische digitale Start-ups wurden sowohl von menschlichen Experten als auch von einem Modell der künstlichen Intelligenz analysiert. Unter Verwendung einer unscharfen additiven Verhältnisbewertung wurde jedes Start-up auf einer Fünf-Punkte-Skala bewertet und die Ergebnisse mit dem FAST 50-Ranking von Deloitte verglichen. Die Ergebnisse wurden mit dem FAST 50-Ranking von Deloitte verglichen. Die Bewertungen der künstlichen Intelligenz und der Menschen unterschieden sich, wobei die Menschen mehr Wert auf die Erfahrung des Gründers und die Attraktivität des Produkts legten. Die Studie schlägt einen Bewertungsrahmen vor, der sowohl menschliche als auch KI-Expertise für den interaktiven Vergleich und die Aktualisierung umfasst. Der Artikel unterstreicht den Wert der KI bei der Bewertung von Start-ups und betont die Notwendigkeit, menschliche und künstliche Intelligenz bei der Entscheidungsfindung zu vereinen.

FRAMEWORK DO WYCENY START-UPÓW CYFROWYCH Z WYKORZYSTANIEM SZTUCZNEJ INTELIGENCJI I ZBIORÓW ROZMYTYCH

Niniejszy artykuł przedstawia innowacyjny framerok do wyceny inwestycji w cyfrowe start-upy przy użyciu zbiorów rozmytych. Framework uwzględnia jako kryteria oceny merytoryczną wiedzę założyciela, zbywalność produktu, kondycję finansową i obecność w mediach społecznościowych. W ramach badań przeanalizowano cztery czeskie start-upy cyfrowe, wykorzystując w tym celu zarówno ludzkich ekspertów, jak i sztuczną inteligencję. Każdy start-up oceniono w pięciopunktowej skali, a wyniki porównano z rankingiem FAST 50 firmy Deloitte. Oceny AI i ludzi różniły się, przy czym ludzie kładli większy nacisk na doświadczenie założyciela i atrakcyjność produktu. W artykule zaproponowano framework, który interaktywnie łączy ocenę przeprowadzaną przez ludzkich ekspertów i sztuczną inteligencję.