Group Decision Support Model for Tech-Based Startup Funding Using Multistage Fuzzy Logic

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The startup business model has grown rapidly in the last few years. However, giving investment or funding to a startup, especially in its early stages, is difficult because the risk is higher than a conventional company. This paper proposes a group decision support model (GDSM) that can help both government venture capital (GVC) and private venture capital (PVC) make the right funding decision. The model was built using a simple mathematics method (SMM) and multistage fuzzy logic (MFL) to examine twenty-two parameters in fuzzy and nonfuzzy values. Two experts from GVC and PVC were interviewed to weigh all the parameters. The model is implemented and tested using three real-world data. Ultimately, the model can help decision-makers in GVC and PVC to decide the most optimum funding for startups.

Povzetek: Članek predlaga model podpore skupinskih odločitev (GDSM), zgrajen z uporabo metode SMM in mehke logike.

1 Introduction

The connection between technology and entrepreneurship is more robust than ten to twenty years ago. It gave birth to many new startups, primarily in technology. So many companies have become more prominent because they have adopted technology in their business process [1]. The definition of a startup is a new coming company trying to launch a new product in the market. Commonly, startups are still trying to show their existence and face high failure risks. Because of that, the main objective of a startup is to find a repeatable and scalable business model. The business model that startups adopt differs from the traditional business planning that a large firm commonly uses. A startup has no experience, so it is necessary to overcome numerous transitions for its growth and maturation [2]. Many new businesses that use technology appeared in the last ten years, for example, online motorcycle taxis for traveling, e-commerce for shopping, and loan provider service that positively impact many people. The growth of startups brings up a new disruption in the business world. Many startups are rapidly growing and have managed to be leaders in the field in which they participated. That successful startup often forces the pre-existing company to close its business.

Behind massive startup growth, it turns out that the startup business model also faces many challenges. Commonly a startup will face risk from five perspectives: market, product, competitiveness, people, and finance [2]. Research says that startup business models have a 40% higher risk than the other business models, which causes nine of ten startups to fail before turning three and still have a high risk until they are five [3]. A survey that analyzed 3200 startups in 2012 shows that 29% of the failed startup were caused by a rainout of cash [4]. Many brilliant ideas cannot be realized because they do not have enough money. From that problem, venture capital (VC) comes to help, mainly by providing funding. Besides that, VC will also help startups grow faster, produce more value, and generate more employment and innovation. It shows that a VC can play a very crucial role in the success of a startup [5]. The main reason VC plays a more significant role in the growth of a company is caused by the fact that most startups only have a small fund to grow their business. In contrast, that startup needs an enormous fund to develop their idea into a product. That is why the number of VCs is also continuously increasing.

Before funding a startup, the VC needs to know the potential of that startup to be successful. It can be done by analyzing and evaluating several factors that can indicate the success of a startup. It ensures that VC does not invest its money in the wrong startup. The high failure risk forces every VC to measure the potential startup correctly before investing in a startup. Many VCs suffer heavy losses due to wrong investment decisions. From that problem, this research proposes a solution that can help VCs measure the feasibility of a startup receiving funding and suggest the amount of funding that should be given based on some supporting parameters.

In this research, the GDSM with MFL is proposed to achieve the purpose of helping every decision-maker make a better decision. Research in the decision support model (DSM) fields about startup funding were performed in 2016. That research was purposed to choose a decent company to receive South Africa GVC funding. It uses *intuitionistic fuzzy* (IF) and technique for others' preference by similarity to ideal solution (TOPSIS) to select potential startups. The study also said that many contributions could be made in future research, like using another method, using different parameters, or generating a model that can be used for GVC in another country [6]. As can be seen, that research focused on creating a DSM for South African GVC, which cannot be used for PVC and GVC in another country. New research needs to develop a model to help both PVC and GVC make decisions because both VCs have different perspectives on measuring potential startups. For example, PVC maximizes financial profit and avoids risk, while GVC maximizes social impact and tolerates considerable risk [7].

This research focuses on creating GDSM that PVC and GVC can use to suggest the funding amount from both perspectives based on some parameters. MFL is also be used to model subjective and intuitive factors obtained from the parameters to make the best decision. The proposed model can determine if a startup is feasible or not to receive funding, accompanied by the number of funds that the startup can receive. This research can help many PVCs and GVCs make the right decisions by measuring startups objectively. Also, this research is expected to give a new reference, especially in the DSM, FL, and startup fields.

2 Literature review

2.1 Related works

Study about company funding decisions has been done several times. Some initial research uses a different method to calculate the right funding amounts. Much-preceding research still focuses on investment or funding decisions in a public company, especially one already listed in the stock market. Research about startup funding from preliminary stages is hard to find because the startup business model is new, and factors that affect the number of funding amounts are often changing. This research uses the VC perspective and gains the specific parameters for PVC and GVC to suggest the best funding amount. Below are some related works that can inspire this study. The conclusion from the related works can be found in Table 1.

In 2016, the initial research had the most influence on this research. The study develops a DSM that uses intuitionistic fuzzy techniques for TOPSIS multi-criteria decision-making to measure the company funding feasibility from the South African GVC perspective. It uses six criteria (team personality, team experience, product potential, financial, market, and social impact) and twenty-seven parameters from five startup businesses and four decision-makers. Every criterion was analyzed using fuzzy TOPSIS. This research can model subjective measurement very well by using FL. It can be a system that can increase fairness and transparency in selecting feasible startups, especially for early-stage startups with high potential [6]. The limitation of this research was that the proposed model could not fit the PVC requirement and GVC point of view in another country.

In 2017, another research about funding eligibility was performed. The study uses DSM based on FL Tsukamoto to assess funding eligibility for small-medium enterprises (SMEs). The parameters were gathered from observation and interviews, and the result was tested in an Islamic microfinancing company. There are four criteria: assurance, business, ability, and character. The criteria were classified using Tsukamoto FL using five ratings for the MF [8]. This research only shows the system design without the proposed method's result. It cannot clearly show the result of implementing the model. The criteria used in the paper are also too general and too least. However, it claimed that the fuzzy model could provide more flexible results in making a decision.

In 2018, research was performed to select promising enterprises from a VC point of view. It uses intuitionistic fuzzy Prospect theory (IFPT) to simulate the intuition and psychological state VCs commonly use when making an investment decision. The proposed method was tested in Ali Capital to select promising enterprises in China and show that IFPT has more advantages than TOPSIS. This method results in a rank of promising enterprises obtained from the value and weighting functions. It helps VC make decisions based on intuition and psychological states [9]. This research shows that the result has better advantages than using TOPSIS. It cannot be compared fairly with the research from [6] because it uses TOPSIS for GVC and IFPT for PVC. Both pieces of research can have much influence on this research. However, this paper does not show the criteria and parameters used for decision-making.

In 2020, a probabilistic hesitant fuzzy element (PHFE) with regret theory and water-filling theory was used to select potential investment projects from several startups in China. It analyzes four criteria: management team, financial situation, market condition, and product & service. The model was tested in four investment projects in China then some venture capitalist group was invited to assess that project [10]. The result of this study is compared with the TODIM method and shows that both ways result in the same alternative ranking. Then when implementing PHFE with regret theory, it still shows the same positive results. This paper concentrated on objectively identifying all used criteria and parameters in a PHFE.

Table 1: Related work conclusions

Cite	Method	Parameter (Input)	Result (Output)
[6]	Developing a **DSM** using **Fuzzy Intuitionistic** with **TOPSIS.**	Use six main criteria (personality, experience, potential, financial, market, and social impact) with twenty-seven parameters.	This study results in a DSM that can reduce GVC unfairness and non-transparency in funding selection for potential startups.

[8]	Developing a **DSM** using **FL Tsukamoto**.	Use four main criteria: assurance, business, ability, and character (No detailed information for the parameter).	This study can help SMEs by providing flexible results to help decision-makers decide and get alternative results.
[9]	Using **Intuitionistic Fuzzy Sets Prospect Theory (IFSPT)**.	Using four main criteria heavily relied on intuition and psychological state (No detailed information for the parameter).	This study helps VCs handle intuition and psychological decisions in selecting potential startups. It gives a new perspective to determining investment decisions
[10]	Using **Probabilistic Hesitant Fuzzy Element (PHFE)** with **Regret** and **Water-Filling Theory**.	Use four main criteria: management team, financial, situation, market condition, and product & service (No detailed information for the parameter).	The study helps VC select potential SMEs by combining PHFE with two nonlinear mathematical models and comparing the result with previous research that uses TODIM.

There are many approaches to making a funding decision from the related work. Most of the approaches to making funding or investment decisions use FL. The implementation of FL can handle qualitative or subjective values that cannot be handled using the analytical method. Some methods like TOPSIS or PHFE are proposed to make the best funding alternative. Most studies cannot help decision-makers decide based on the alternatives gathered clearly. Also, a system that can help many decision-makers, especially VCs, is rarely found.

A GDSM must be proposed to solve startup funding decisions from PVC and GVC perspectives. A model with the FL method can work very well to solve many decision-making problems, especially when the parameters used are qualitative, like funding a startup. It gives this research much room and a chance to propose a system that can help many decision-makers make the right decision based on FL methods. The implementation of DSM for investment or funding purposes is already implemented in China PVC [9] and South Africa GVC [6], which positively impacts VCs in maximizing their investment and minimizing risk.

2.2 Decision support model

The DSM is a solution to help decision-makers decide by building a scientific model to analyze some parameters that affect the decision [11]. The decision produced by DSM must be objective, logical, and scientifically accountable [12]. DSM is often used to make strategic decisions, especially in business. The initial study of DSM aims to take information from many business functions, such as billing, payroll, and inventory control, to make it worthwhile for decision-making [13]. In the early development of DSM, especially in the late 1970s, many decisions from DSM could not satisfy the decision-maker because of the poor hardware capability, which resulted in low-quality decisions. However, in the early 2000s, when the computer industry started to overgrow, the DSM became popular again, making many decision-makers enthusiastic about implementing innovative DSM projects [14]. Fig. 1 shows the process of DSM creation.

DSM can solve many problems, such as planning for agriculture and farming [15], selecting sustainable suppliers [16], improving tourism logistics and public transportation [17], making purchasing decisions [18], or even solving recent issues such as handling COVID-19 [19]. Moreover, a DSM can also help to solve a once-in-a-lifetime problem, such as moving the Indonesian capital city that asks humans as a decision-maker to analyze and learn deeper based on many parameters. Making that kind of decision is challenging because it should not be wrong, which may cause many new problems if wrong [11]. Commonly management information systems (MIS) and DSM are considered the same. However, in practice, both are different. MIS is best used to identify business problems and is not aimed at supporting the decision-making of an individual or group. In contrast, DSM can help the specific needs of an individual or group to support decision-making [20]. DSM has three characteristics as a supporting system [14] which are:

1. DSM is to help decision-making processes.
2. DSM must support decision-makers, not change decision-makers roles or even automate the decision-making process.
3. DSM must be able to transform when the decision-making process needs to change.

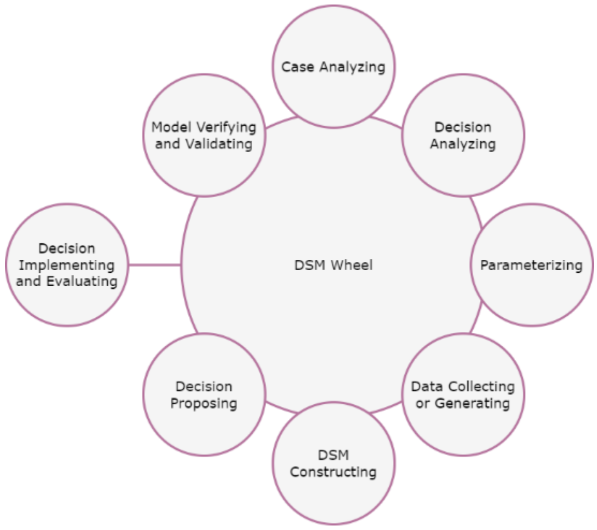

Figure 1: DSM Wheel [11]

2.3 Group decision support model

A decision-making problem can be classified in many ways. One of the most popular ways to classify is based on the number of decision-makers contributing to that decision. There are two classes: single decision-maker and group decision-maker. The main difference between the two classes is that a single decision-maker only needs one responsible for defining the problem and assessing the alternative. In contrast, group decision-makers need more

than one to define a problem and evaluate alternatives. It can be done by collecting and aggregating the process.
Nowadays, many problems rely on group wisdom instead of single individuals, making the GDSM more critical, especially for business, politics, and management decision-making [21].

The communal problem in building GDSM is aggregating individual preferences into a distinct group. Some techniques can express group decision-maker preferences, such as classical pairwise comparisons or new bilateral agreement techniques [22]. The diverse backgrounds, thinking processes, and knowledge of each decision-maker give other challenges in making a collective decision. It becomes more complex to analyze each preference than a single decision-making process [21]. From that problem, GDSM can help decision-makers to make the right decision for many decision-makers.

2.4 Fuzzy logic

In making a decision, many parameters are used to produce an alternative. The parameters are divided into two types: subjective and objective. The subjective parameters are commonly biased and ambiguous. From that problem, FL helps transform bias and ambiguous values into precise values that computers can use. A computer cannot understand the value of the parameters collected if the value is not precise [23]. FL makes a computer understand the bias parameters by understanding the value, not as a precise value but as a bias value. Traditional logic uses '0' and '1' to describe the true and false parameters. While FL represents the parameters using a value from '0' to '1'. FL does not represent a value that uses '0' as a false and '1' as a true, but it can give a degree of truth (DoT), such as '0.7 true' and '0.3 false' [11]. FL implementation can be found in many fields, such as in the economic assessment of wind power [24], for selecting the optimal project in portfolio management [25], or to be implemented with novel algorithms such as butterfly lifecycle algorithms for measuring company growth performance [26].

Using the fuzzification process, the FL changes crisp input into a fuzzy value. After that, the fuzzy value will be transformed into a precise value (crisp output) using the defuzzification process [12]. A linguistic variable (LV) should be declared for the fuzzification process. For example, performance can be categorized into Very Bad, Bad, Normal, Good, and Very Good. After that, a membership function (MF) should be created, representing the DoT from the LV. After creating MF, a DoT can be gathered using *linear interpolation*, resulting in fuzzy values. After that, a defuzzification process will produce a crisp output. One of the most popular methods to calculate crisp output is using the *center of gravity*. Fig. 2 shows the primary step of the FL algorithm.

2.5 Multistage fuzzy logic

Complex problems like startup funding decisions require many categories with many parameters. Fuzzifying all parameters simultaneously becomes difficult because the fuzzy process requires many fuzzy rules. From that problem an MFL can simplify that problem. Rather than fuzzifying all the parameters, the MFL can be designed to fuzzify the parameters into several stages. Many researchers agree that a multistage system makes fuzzy design easier by reducing complexity [27].

Commonly the MFL process is executed in two stages. The first stage fuzzifies all parameters, while the second stage fuzzifies all categories. Both stages can use different fuzzy inference systems (FIS), but the most popular is Mamdani FIS. The use of MFL not only reduces the complexity but also has many other advantages. One example is that the MFL makes the model more modular. The decision-makers can find the result or score from each parameter and category. The implementation of MFL can be found in many problems, such as in evaluating wastewater treatment systems [28], improving voltage stabilization effectiveness [29], or simply evaluating student performance [30].

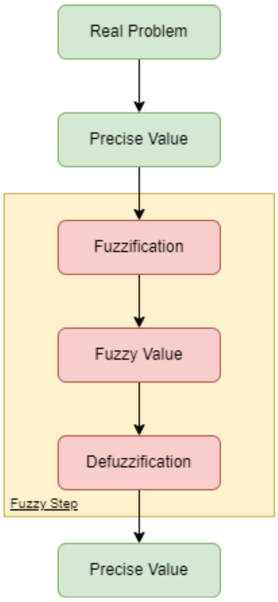

Figure 2: FL Algorithm

3 Research methodology

The model was created following seven steps of the DSM wheel frameworks. A DSM wheel ensures the model is well-developed and can produce helpful suggestions. However, the research performed one cycle of the DSM wheel. Because of that, a linear DSM creation process was used to illustrate the DSM creation process. An observation and literature study helped analyze the case and find a decision alternative. Then, a literature study was performed to ensure all selected parameters were correct. After the parameters were firmed, the data for this model was collected and gathered from many sources on the internet. Then the essential part of the research is to create a model. The model was created using a method that can process all the parameters, in this case, by using MFL. The method must be carefully chosen to make the correct model and ensure the proposed decisions are correct. The model resulted in a decision that can help the decision-maker. Later in the DSM process, two options can be chosen after proposing the decision: *implementing & evaluating* or *verifying & validating*. In this research, *verifying & validating* are chosen to prove the correctness of the models. Fig. 3 shows the research stages influenced by the linear DSM creation process.

The first step is *case analyzing*. Understanding a case or a topic in DSM becomes one of the most crucial things. The step seeks knowledge as much as possible to be the foundation for making a model. The knowledge obtained from the case analysis step can help the researcher to build a proper model. The researcher is expected to understand the chosen topic fully. A high understanding of the topic can be a central starting point for research success [11]. This step involves observation and literature study to find the current problem. The process starts with observing some trending topics and their problems on the internet. After observing, an exciting topic is found: startup funding.

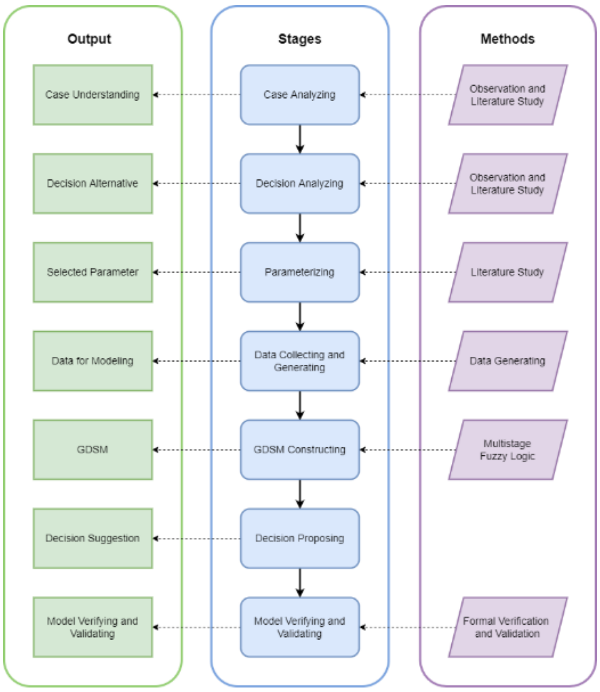

Figure 3: Research stages

After getting the case, the second step is *decision analyzing*. This step was to find what kind of decision to solve and how many alternatives could occur. It was done by doing observation and literature study. The final decision that this research tries to solve is about startup funding amount. The alternatives for final decisions are obtained by doing a literature study. At first, this research was given an alternative in the form of funding commonly used in the funding round. That common alternative is divided into Pre-Seed, Seed, Series A, Series B, and Series C [31]. However, after observing and reviewing more papers, no standards determine how much funding series a startup can receive.

Moreover, in some cases, the funding series are not finished in Series C (IPO Preparation). For example, Indonesia's ride-hailing company received series F funding in 2018-2020. The amount from each series can also differ depending on the country, law, and other factors. This research categorized 'Pre- Seeding' into 'Seeding.' Then, all funding series after 'Series C' were categorized into 'Series C.' Table 2 shows the funding type and amount in USD.

Table 2: Decision alternative

Funding Type	Amount of Funding
Seeding	$0 - $2,000,000
Series A	$2,000,000 - $15,000,000
Series B	$15,000,000 - $60,000,000
Series C	$60,000,000 - $100,000,000

The third step is *parameterizing*. In the model, the parameters and their weight significantly impact the most optimum funding amount result. Because of that, all parameters and their weight need to be wholly discovered before starting to build the model. All the parameters used are acquired in *parameterizing* stages. PVC and GVC use the exact parameters, but they all have their weight based on PVC and GVC perspectives. In making a decision, both PVC and GVC use the same parameters, but the difference lies in the primary purpose. For example, PVC tends to be focused on maximizing profit, while GVC uses other goals, such as promoting entrepreneurship or supporting innovative ideas [32]. This *parameterizing* activity contains three main steps: identify the parameters, define the value from each parameter, and weigh the parameter from PVC and GVC perspectives. The first step consists of three activities: finding as many papers as possible, doing a deep analysis, and categorizing the parameters.

The fourth step is *data generating*. The data was gathered from any source, such as a journal, research paper, magazine, or the internet. In this research, the possible source comes from the internet. Because the current and actual data can only be found using the internet. Some credible websites that provide startup data are *Crunchbase*, *Pitchbook*, and *VentureSource*. Some parameters data, such as government or political support, may be changed anytime. Because of that, the data and the model created are focused on current conditions. Ultimately, the data must be cleaned up to ensure that data has excellent quality and is suitable for the DSM construction process.

The fifth and sixth step is *model constructing* and *decision proposing*. In the *model constructing* step, the model was developed. It uses an apparent flow of DSM, which is *input-process-output*. The model uses Python because it has many advantages, especially the available libraries that can ease the coding process. The model can be accessed using a web-based application. The decision-makers can input the value from all parameters to the model and get the result from the model that can help the decision-maker make funding decisions.

In the last step, *model verifying & validating* were used to evaluate the model. This step is not to judge the decision, and it is not to find whether the decision is right or wrong. The verification process measures how true the model is based on the theory about the selected cases. The validation process measures how accurate the data is in the model compared to the actual case. In this research, the verification step verified three factors: parameters, preprocessing process, and FL process. The validation process covers two factors: the input and output data.

4 Results and discussion

4.1 Decision parameter

The parameter used in the model is obtained by following the *parameterizing* steps. After a literature review, 22 decision parameters are used to produce the final funding decision. All the parameters are obtained from twelve papers. In the model, both PVC and GVC use the exact parameters in deciding the most optimum funding amount. However, the weighting difference causes the funding results to differ between PVC and GVC. All 22 decision parameters are also divided into six categories.

Each parameter also has its value range. For example, the 'startup age' parameters range must be between 0 to 10. The model will reject the input when the input is smaller than 0 or larger than 10. There are two types of values: fuzzy and nonfuzzy. All numeric values are classified into fuzzy, and all categoric values are classified into nonfuzzy. There are fifth-teen fuzzy parameters and seven parameters that are nonfuzzy. The fuzzy parameters are 'startup age,' 'location,' 'continuous development,' 'expense,' 'total previous funding,' 'total funding round,' 'distribution,' 'market size & demand,' 'competitor,' 'response,' 'product advantage,' 'team innovation,' 'team skill & knowledge,' 'IT infrastructure & resource,' and 'IT innovation & strategy.' The nonfuzzy parameters are 'politic,' 'strategy,' 'competency,' 'dedication,' 'experience,' 'personality,' and 'product innovation.' The description of all parameters and their value are described in Table 3.

Table 3: Startup funding detail

Parameter	Description	Value
Startup Age	The age of the startup.	0 – 10.
Location	Distance between the head office and the place where the business process happens.	0 – 1000 (in kilometer).
Politic	Support from governance for startup and its environment in a country.	1: No support from governance. 2: There is support from governance in the form of funding assistance. 2: There is support from governance in a startup development program. 3: There is support from governance through funding assistance and a startup development program.
Strategy	Current startup strategy.	1: In the development phase (usually still in the 'cash burn' strategy). 2: In the transition from the development phase into the profit-oriented phase. 3: Fully focused on finding profit (usually, the startup will focus on IPO preparation).
Continuous Investment	The number of investors that currently invested in that startup.	0 – 20.
Expense	Expenses and debt that the startup currently had.	0 – 10,000,000 (in USD).
Total Previous Funding	Total of funding that a startup has already received.	0 – 100,000,000 (in USD).
Total Funding Round	Total funding series from a startup. It also counts funding from an accelerator or incubator.	0 – 10.
Competency	The latest education from the founder.	1: School 2: Bachelor's 3: Master's 4: PhD
Dedication	Founder participation in the startup world.	1: Never be a speaker or mentor. 2: Actively being a speaker at startup events. 2: Actively being a mentor in a startup development program. 3: Actively being both a speaker and mentor.
Experience	The founder's experience in related business fields and the startup environment.	1: No experience in related fields. 2: Has been working in related fields. 3: Has been created a startup. 4: Has been running a startup for more than three years.
Personality	The founder's personality and reputation. It can be seen in news articles.	1: Bad 2: Neutral 3: Good
Distribution	The way to distribute the product. It measures effectiveness and easiness. It can be seen from monthly traffic.	0 – 50,000.
Market Size & Demand	The potency of the market and the demand for the product. It can be seen in the potential customer.	0 – 10,000,000.
Competitor	Count of competitors that compete in the same/similar business field.	0 – 10.
Product Innovation	The innovation of the product/service. It commonly measures the uniqueness of the product/service.	1: Same product/service can be found. 2: Similar product/service can be found.

		3: No similar product/service can be found.
Response	The impact of the product on the user. It measures user satisfaction from app stores.	0 – 5.
Product Advantage	The advantage of the product compared to the other product in the market that makes a product become competitive.	0 - 3 +1: Patentable. +1: Supported by big firms. +1: Supported by governance.
Team Innovation	The team's ability to absorb and implement recent technology. It can be seen from the number of open-source projects from that startup.	0 – 3.
Team Skill & Knowledge	The average of years' experience from the team. The minimum years of experience in tech team job requirements can also be seen.	0 – 5.
IT Infrastructure & Resource	The amount of technology used.	1 – 50.
IT Innovation & Strategy	The scalability potential of the product.	0 - 6 +1: Using cloud computing. +1: Using microservice architecture. +1: Using frameworks from Top 10 Framework Technology Stackoverflow 2022. +1: Using databases from Top 5 DB Stackoverflow 2022. +1: Using Docker. +1: Have mobile apps.

As mentioned, all the parameters must be weighed because each parameter has different weights in determining the right funding amount. For example, 'location' parameters have a minor influence compared to 'product innovation' parameters. Some of the most popular methods to do the weighting process in parameterizing are observation, literature review, and interview to gain expert judgment [11]. For this research, interviewing an expert is chosen because the judgment is better if it comes from an expert in the field. Some researchers also started implementing multi-expert judgment the model because the model can produce better decisions [33].

Two experts are interviewed, one from PVC and one from GVC, to weigh the parameters. They were asked to rate the importance of the parameter using the direct rating method by using a range from 1 (not important) to 10 (very important). This type of weighting is easy because it can easily alter the importance of parameters without adjusting the other parameters [34]. After getting the weighted result, the final weight is obtained by normalization because the process improves the model performance. The normalized data handles outliers better by minimizing standard deviation [35]. Then, for the second stage, the weight comes from the sum of every parameter weight in each category. The weighting result for all twenty-two parameters (for the first stage) is displayed in Table 4, and then for all six categories (for the second stage) is shown in Table 5. In the table, the 'count' column represents the judgment from the expert (range 1 to 10). Then the 'weight' column represents the normalization result by dividing the value of parameter count (stage 1) or category count (stage 2) by the total of 'count.' The weight can represent the perspective from both VCs. For example, the weight of the 'startup age' parameter from PVC is 0.040, while from GVC is 0.006. That weight represents the theory where PVC focuses on reducing risk by finding mature startups while GVC can deal with higher risk by acting fine with early-stage startups [3]. In both tables, all the values are rounded (the calculation in the model uses precise values). Later, the PVC and GVC weighted parameters were transformed into a fuzzy rule and utilized for calculation in the model.

Table 4: Funding parameter weight (1st stage)

Parameter	**PVC**		**GVC**	
	Count	**Weight**	**Count**	**Weight**
Startup Age	6	0.040	1	0.006
Location	3	0.020	1	0.006
Politic	7	0.046	8	0.052
Strategy	9	0.060	10	0.065
Continuous Investment	8	0.053	6	0.039
Expense	8	0.053	6	0.039
Total Previous Funding	9	0.060	10	0.065
Total Funding Round	8	0.053	8	0.052
Competency	8	0.053	10	0.065
Dedication	6	0.040	4	0.026
Experience	6	0.040	10	0.065
Personality	7	0.046	4	0.06
Distribution	5	0.033	5	0.032
Market Size & Demand	9	0.060	10	0.065
Competitor	9	0.060	10	0.065
Product Innovation	6	0.040	8	0.052
Response	4	0.026	8	0.052
Product Advantage	7	0.046	8	0.052
Team Innovation	6	0.040	8	0.052
Team Skill & Knowledge	6	0.040	8	0.052
IT Infrastructure & Resource	7	0.046	6	0.039
IT Innovation & Strategy	7	0.046	6	0.039
Total	151	1.000	155	1.000

Table 5: Funding parameter weight (2nd stage)

Criteria	**PVC**		**GVC**	
	Count	**Weight**	**Count**	**Weight**
Business	25	0.166	20	0.129
Financial	33	0.219	30	0.194
Founder	27	0.179	28	0.181
Market	23	0.152	25	0.161
Product	17	0.113	24	0.155
Resource	26	0.172	28	0.181
Total	151	1.000	155	1.000

4.2 Raw data

The data used for model simulation is acquired in the *data collecting and generating* process. Three pieces of data are used in the model simulation, shown in Table 6. All data collected in this process have come from the real world, gathered from many sources on the internet. Most of the data cannot be found in other sources than on the internet because the data is actual. However, the *data collecting and generating* examples in this section use only Startup A as an example. Startup A is a new company in the food and beverage industry. It serves many kinds of coffee through a fleet of electric mobile cafes. The data used for Startup B is an aquaculture company that offers an internet of things (IoT) system for shrimp farming to achieve a more sustainable business. Then, Startup C is a startup with numerous services focusing on transportation and delivery using motorbikes. The data used in the model must not be processed, which means the data must be in the raw format.

Table 6: Raw data

Parameter	Startup A	Startup B	Startup C
Startup Age	2 years old	6 years old	10 years old
Location	0 km	35 km	0 km
Politic	3	3	3
Strategy	2	3	3
Continuous Investment	6	9	20
Expense	0 USD	0 USD	95.6M USD
Total of Previous Funding	2.4M USD	12M USD	100M USD
Total of Funding Round	2	6	10
Competency	3	2	3
Dedication	1	2	3
Experience	2	4	4
Personality	2	3	3
Distribution	700	7,715	37,107
Market Size & Demand	4,095,000 people	1,830,000 people	10,000,000 people
Competitor	10	1	4
Product Innovation	2	2	1
Response	5.0	4.6	4.6
Product Advantage	1	2	2
Team Innovation	0	0	3
Team Skill & Knowledge	2.5 years	2 years	3 years
IT Infrastructure & Resource	11	15	15
IT Innovation & Strategy	3	5	6

4.3 System design

After selecting parameters and knowing the data type, a method is discovered. It is already mentioned before that the model uses MFL because most of the parameters can be turned into fuzzy values. Another reason for using MFL is that there are 22 parameters used in this research, making the FL process more difficult if all parameters are executed in a single process. The first stage uses FL to produce the category value by executing FL for all parameters in a category. Then the second stage uses FL to produce the funding amount based on all categories. The connection between parameters and the methods is described using the class diagram. A class diagram is a universal notation describing all technical contribution objects in all research domains [12]. A class diagram can effectively describe many entities, data, and methods used in the modeling process.

In the class diagram, the 'Startup' class consists of all 22 parameters previously mentioned in Table 3. Because all the parameters must be processed using FL, the class diagram shows the connection between the 'Startup' class and the 'Fuzzy Logic' and 'SMM' classes to produce a funding decision. The class diagram also shows FL components, such as the 'Membership Function' and 'Fuzzy Rule.' The 'Membership Function' consists of LV and DoT with two inheritances: 'Trapezoidal' and 'Triangular.' The 'Fuzzy Rules' class is used in the 'fuzzify-fuzzy-defuzzify' process and consists of 'frbid' for the fuzzy rule base identifier and the fuzzy rules itself. The 'SMM' class consists of nonfuzzy weight to calculate the nonfuzzy value with nonfuzzy weight. The result from the FL helps PVC and GVC make a funding decision by giving the decision-makers the amount suggested and the funding type. As shown in the 'Funding Decision' class, the calculation and the results for PVC and GVC differ. The complete class diagram for the constructed model can be seen in Fig. 4.

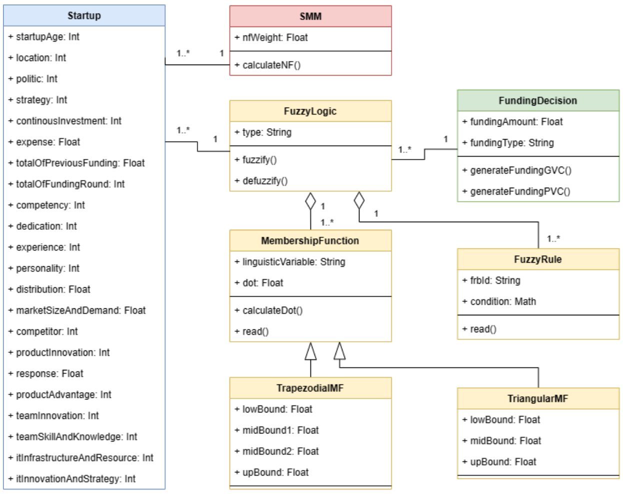

Figure 4: Model class diagram

4.4 Model & algorithm

This section describes the process and the algorithm from the model. As mentioned, the model provides an alternative for multiple decision-makers, as shown in the use case diagram in Fig. 5. Because of that, the process is executed twice (or more) to provide an alternative for all decision-makers. The overall process is reading data, preprocessing data, processing fuzzy input with first stage FL, processing nonfuzzy input with simple mathematical method (SMM), processing the second stage FL using the output from first stage FL, and aggregating the output. An activity diagram in Fig. 6 depicts the algorithm from the model.

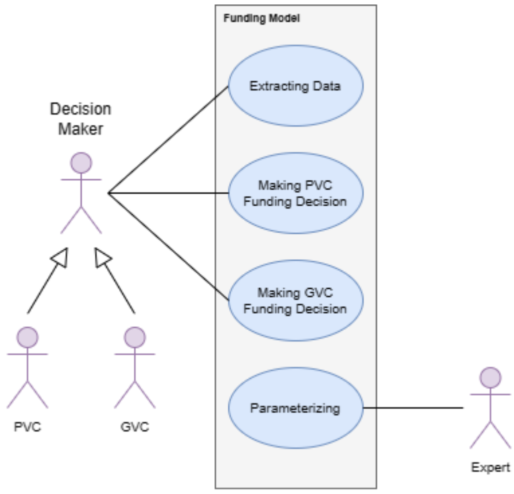

Figure 5: Model use case diagram

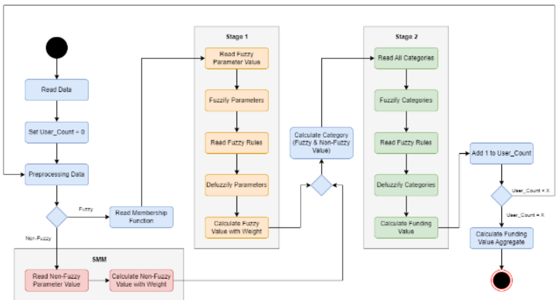

Figure 6: Model activity diagram

The process begins with reading the raw data from the data collecting and generating process shown in Section 4.2. All the data must be in raw format and not be preprocessed before entering the model. After that, the model declares the user count variable as zero. The number of users is used to calculate the funding aggregate in the last step of the process. In this case, the final value of the user count variable is two (PVC and GVC). Then, because the data is in raw format and have different forms and value ranges, all data need to be preprocessed by doing data normalization using (1) to ensure all data are in the range 0 to 1. After that, some data must be inversed using (2).

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin} \quad (1)$$

$$Xinv = 1 - (Xnorm) \quad (2)$$

After data preprocessing, the process is divided into two processes based on the data type (fuzzy or nonfuzzy). For nonfuzzy values, all data is processed by using SMM. It is directly multiplying the data with the weight from Table 4. For fuzzy values, all data is processed following the 'fuzzifiy-fuzzy-defuzzify' process. The model processes all fuzzy values using Mamdani FL in both stages. There are many reasons to implement MFL in this research than conventional FL. The fundamental thing that makes MFL important is the number of parameters used in the model. From the parameterizing stages, 22 parameters affect the funding decision. Doing a conventional FL for that number of parameters is almost impossible because that number of parameters can produce thousands of FRB combinations. The simplified FRB is also difficult to implement because it is hard to maintain consistency in making the FRB. Even though the FRB is implemented, the computing time for that amount of FRB becomes incredibly long, making the decision-making process inefficient. The implementation of MFL also has many advantages. One of the most important advantages is that the model can show the values for each category rather than only showing the final output. It can give more information to the decision-maker by showing the result from every category.

Two things need to be created for the fuzzification process. The first is to create an LV, and the second is to create MF. Both LV and MF need to be created for all antecedent and consequent. An LV can be created by categorizing all fuzzy parameters and categories. For example, the LV for the 'location' parameter can be categorized into 'near,' 'medium,' and 'far.' After creating LV, the next step is to create an MF to map the LV with the DoT. The MF for this model uses a combination of triangular and trapezoidal shapes.

In this model, there are four types of MF scale. The first scale is low (0.0, 0.0, 0.3, 0.5), moderate (0.3, 0.5, 0.7), and high (0.5, 0.7, 1.0, 1.0). It is used in the 'startup age,' 'market size & demand,' 'product advantage,' 'team innovation,' 'team skill & knowledge,' 'IT infrastructure & resource,' and 'IT innovation & strategy' parameters. The first scale is also used in categories. The second scale is low (0.0, 0.0, 0.2, 0.5), medium (0.2, 0.5, 0.8), and high (0.5, 0.8, 1.0, 1.0). It is used in the 'location' and 'expense' parameters. The third scale is low (0.0, 0.0, 0.2, 0.3), medium (0.2, 0.3, 0.4), and high (0.3, 0.4, 1.0, 1.0). It is used in 'continuous investment,' 'total of previous funding,' 'total of funding round,' 'distribution,' and 'competitor' parameters. The fourth scale is low (0.0, 0.0, 0.5, 0.7), medium (0.5, 0.7, 0.9), and high (0.7, 0.9, 1.0, 1.0). It is used in the 'response' parameters.

After getting the LV and MF, the fuzzification process can be performed by calculating DoT values to represent the fuzzy values. The DoT values can be obtained by mapping all crisp input with MF. It can be processed using *linear interpolation* in (3).

$$Y = Y1 + \frac{Y2 - Y1}{X2 - X1} + (X - X1) \quad (3)$$

After getting DoT values, a fuzzy rule base must be applied to analyze the correlation between each parameter. Basic mathematical logic becomes the fuzzy rule base fundamental [11]. The rules assess the correlation between each parameter used. The *fuzzy conjunction connection* (AND, ∧) and *fuzzy dis-conjunction connection* (OR, ∨) connect two or more conditions in the fuzzy process. The 'AND' logic is considered true if all conditions are true and considered false if one or more conditions are false. In contradiction, the 'OR' logic is considered true if there are one or more true conditions and false if all the conditions are false. When 'AND' logic is used for fuzzy cases, the minimum value from all conditions is used (4). Otherwise, the maximum value from all conditions is used using the 'OR' logic (5).

This model has two kinds of fuzzy rules based on the judgments from PVC and GVC experts. An example of the rule base for the 'business' category is shown in Table 7. As can be seen, the different outputs for identical inputs come from different judgments from PVC and GVC experts. After getting the fuzzy value, the next step is transforming those fuzzy values into crisp output in the defuzzification process. Defuzzification uses the centroid (center of gravity) equation, as shown in (6).

After getting the result for all categories (fuzzy), the value from each category is multiplied by the weight from Table 4. First stage FL and SMM results are summed up and become the final category values using (7), (8), and (9). The result of that calculation needs to be preprocessed again using normalization, and it serves as input for the second FL stage. The second FL stage produces the final funding amount. The second FL stage has the same FL process as the first FL stage. All categories have the same LV and MF Scale, while the final funding amount has scales like very low (0.0, 0.0, 0.1, 0.3), low (0.1, 0.3, 0.5), medium (0.3, 0.5, 0.7), high (0.5, 0.7, 0.9), and very high (0.7, 0.9, 1.0, 1.0).

Table 7: Business fuzzy rule base (1st Stages)

No	Business		Output GVC	Output PVC
	Startup Age	Location		
1	Mature	Near	High	High
…	…	…	…	…
4	Moderate	Near	High	Medium
…	…	…	…	…
9	Early	Far	Low	Low

$$A \land B = \min(A, B) \quad (4)$$

$$A \lor B = \max(A, B) \quad (5)$$

$$W = \frac{\sum_{i=1}^{n} wi\, Xi}{\sum_{i=1}^{n} wi} \quad (6)$$

$$Fval = \left(FL\, Val. \times \sum FL\, W.\right) \quad (7)$$

$$NFval = \sum (Non\, FL\, Val. \times Non\, FL\, W.) \quad (8)$$

$$Category = \text{Fval} + \text{Nval} \quad (9)$$

In the model, the fuzzy rule base is simplified to reduce the complexity and computing time. There are five main rules. The first main rule is: if five categories have X value, then the output for that rule is very X (very high, medium, or very low). The second rule is: if three categories have X value, then the output for that rule is X (high, medium, or low). The third main rule is: if three categories have a 'high' value and three categories have a 'low' value, then the output for that rule is 'medium.' The fourth rule is: if three categories have 'high' or 'low' values and three categories have 'medium' values, then the output is 'high' or 'low.' The fifth rule is: if two categories have a 'high' value, two categories have a 'medium' value, and two categories have a 'low' value, then the output is 'medium.' The FRB for the second stage is shown in Table 8.

Table 8: Funding amount fuzzy rule base (2nd Stages)

Business	Financial	Founder	Market	Product	Resource	Output
High	High	High	High	High	High	Very High
High	High	High	High	High	Neutral	Very High
…	…	…	…	…	…	…
Low	Low	Low	Low	Low	Neutral	Very Low
Low	Low	Low	Low	Low	Low	Very Low

The defuzzification process uses the centroid (center of gravity) equation, as shown in (6). The final output for the second stage ranges from 0 to 1. Because of that, to transform the value into a funding amount, the output values are multiplied by 100,000,000, so the final output is from 0 USD to 100,000,000 USD. The group result can be aggregated using various methods. There are two types of aggregation in the group decision-making process, which are basic and advanced. Some examples of basic methods are average (arithmetic mean), geometric mean, and harmonic mean. Some examples of advanced methods are fuzzy integral, hybrid aggregation, and linguistic aggregation [36]. This research uses the average (arithmetic mean) to aggregate the result from PVC and GVC. The aggregation process does not use weight because the weight is already implemented in the FL stages and does not need any weighting process in the aggregation steps. In making group decision making, aggregation using the arithmetic mean method has also become the third most popular method after the choqued integral method and linguistic method [36].

4.5 Model simulation

Raw data from Table 6 is used to simulate the model. As mentioned before, the model can be used by two decision-makers. Because of that, the first MFL calculates the funding amount from PVC, and the second MFL calculates the amount from GVC. All the model algorithms follow the algorithm from section 4.4. The process begins with reading all the data from user input. All the input data need to be preprocessed by performing data normalization. The model validates whether the input value can be processed. It divides the input value by the maximum value of the parameters (1). Some parameter values also need to be inversed by using (2). The result of data preprocessing can be seen in Table 9.

Table 9: Data preprocessing result

Parameter	Max. Value	Inversed	Startup A	Startup B	Startup C
Startup Age	10 years old	No	0.200	0.600	1.000
Location	1000 km	Yes	1.000	0.965	1.000
…	…	…	…	…	…
IT Infrastructure & Resource	15	No	0.734	1.000	1.000
IT Innovation & Strategy	6	No	0.500	0.834	1.000

After preprocessing, the nonfuzzy (categoric) value can be directly multiplied by the weight of the expert. However, the fuzzy (numeric) data must be processed using Mamdani FL before it can be multiplied by the weight. Fifteen fuzzy parameters need to be processed. Table 10 shows all the results from the FL process with the weight, and Table 11 shows the nonfuzzy value with the weight.

Table 10: FL result & weight

Parameter	GVC Weight	PVC Weight	Startup A	Startup B	Startup C
Startup Age	0.006	0.040	PVC: 0.499 GVC: 0.499	PVC: 0.588 GVC: 0.795	PVC: 0.814 GVC: 0.814
Location	0.006	0.020			
…	…	…	…	…	…
IT Infrastructure & Resource	0.039	0.046	PVC: 0.499 GVC: 0.499	PVC: 0.500 GVC: 0.687	PVC: 0.795 GVC: 0.795
IT Innovation & Strategy	0.039	0.046			

Table 11: Non-fuzzy & weight

Parameter	GVC Weight	PVC Weight	Startup A	Startup B	Startup C
Politic	0.052	0.046	1.000	1.000	1.000
…	…	…	…	..	…
Product Innovation	0.052	0.040	0.667	0.667	0.334

After obtaining the fuzzy values, the value for each category can be obtained. As can be observed from the table, some parameters have different weights because there is a difference in the weighting process between PVC and GVC experts. All fuzzy values must be multiplied by the sum of the fuzzy weight values. Also, the nonfuzzy values need to be multiplied by the nonfuzzy weight. After that, to produce category values, the result of the fuzzy (7) and nonfuzzy (8) needs to be summed up using (9). The result from the calculation is shown in Table 12.

Table 12: Category values (1st Stages FL Result)

Category	Startup A		Startup B		Startup C	
	GVC	PVC	GVC	PVC	GVC	PVC
Business	1.101	0.116	0.126	0.141	0.126	0.154
Financial	0.036	0.040	0.097	0.109	0.0.97	0.109
Founder	0.107	0.103	0.140	0.139	0.165	0.165
Market	0.032	0.030	0.030	0.028	0.081	0.076
Product	0.099	0.062	0.116	0.073	0.099	0.060
Resource	0.079	0.086	0.125	0.086	0.144	0.136

After getting the result for all the categories from the first FL process, the process can proceed to the second FL stage. In this stage, the amount of funding from PVC and GVC is discovered. The funding amount ranges from 0 million USD to 100 million USD. There are no differences in designing fuzzy rules for both PVC and GVC. Table 13 shows the result from the second FL stage and the aggregation between the results (using average). For example, the amount for Startup A is 66,104,900 USD from PVC, and 70,000,000 USD from GVC, with an average of 68,052,450 USD. Based on the decision alternative in Table 2, the amount given from PVC and GVC is categorized as 'Series C' funding.

Table 13: Funding values (2nd Stages FL Result)

User	Startup A	Startup B	Startup C
PVC	$ 66,104,900	$ 74,634,500	$ 79,065,200
GVC	$ 70,000,000	$ 77,592,200	$ 79,065,200
Average	$ 68,052,450	$ 76,113,350	$ 79,065,200

4.6 Model verification & validation

Verification and validation are the last steps in creating GDSM based on the DSM wheel. Verification is a process to measure the trueness of the model compared to the theory. At the same time, validation is a process to measure the trueness of the data in the model compared to actual data [11]. Three indicators are used in the model verification process: parameter, preprocessing, and fuzzy logic.

The parameter indicator consists of four sub-indicators that check the model's parameter count (fuzzy and nonfuzzy). The fuzzy parameter based on the references is 15, and then the fuzzy parameter used in the model is also 15. Then the nonfuzzy parameter based on the reference is seven, and the model also uses seven parameters. The model's value range follows the references used in Table 3. In the model, if the input value is not in the range of the value in that table, the model shows an error, and the process cannot be processed. The sub-indicator in parameters in weight, all parameters in the model used the weight to calculation process obtained from references in Tables 4 and 5. Based on this verification result, the verification value for the parameter indicator is 1 (true).

The preprocessing indicator consists of two sub-indicators. The first one is the implementation of the normalization formula. The model's formula is already written using the formula mentioned in the references. Then the second one is the implementation of the inversion formula, also written by following the formula in the references. The fuzzy logic indicator also consists of two sub-indicators. In the procedure sub-indicator, the FL implementation in the model follows the rules already stated in the reference by following the 'fuzzify-fuzzy-defuzzify' process. Then the input value for the FL process must be 0.00 to 1.00, like in the references. This verification shows that the preprocessing and FL indicator verification value is 1 (true). The verification process shows that the model is scientifically and academically verified. Table 4.25 shows the summary of the model verification process.

Table 9: Model verification

Indicator	Sub-indicators	Based on References	Presented in Model	Trueness	Verification Value
Parameter	Fuzzy	15	15	V	1.00
	Nonfuzzy	7	7	V	1.00
	Value Range	Based on Table 3	Based on Table 3	V	1.00
	Weight	Based on Tables 4 & 5	Based on Tables 4 & 5	V	1.00
Preprocessing	Normalization Formula	(1)	(x – xmin) / (xmax – xmin)	V	1.00
	Inversion Formula	(2)	1 – xnorm	V	1.00
Fuzzy Logic	Procedure	Fuzzify, Fuzzy, Defuzzify	Fuzzify, Fuzzy, Defuzzify	V	1.00
	Input Value	0.00 – 1.00	0.00 – 1.00	V	1.00
Total					1.00

All the data input from Startup A, Startup B, and Startup C are validated for the model validation process. All data is in the range that is already described in Table 3. After that, the output value from the model is checked, and the result is that all the output from the GDSM model is in the range of the value in real life. The output for both PVC and GVC is 0 to 100,000,000, so the validation value for the model is 1 (true). The validation process shows that the data used in the model and the result from the model are scientifically and academically correct. Table 9 shows the result of the model validation process.

Table 9: Model validation

Indicator	Value in Real	Value in Model	Trueness	Validation Value
Startup Age (A)	0 – 10	2	V	1.00
…	…	…	…	…
GVC Funding Result	0 – 100,000,000	56,763,500	V	1.00
		66,868,500	V	1.00
		79,296,300	V	1.00
Total				1.00

4.7 Discussion

Compared to related works about startup funding, research from [6], [8], [9], and [10] can only produce funding suggestions from one perspective of decision-makers. The previously created model cannot simultaneously accommodate perspectives from both PVC and GVC. This research offers a solution to accommodate both perspectives in making funding suggestions. Research from [8], [9], and [10] also use a few numbers of parameters which far smaller than the parameters used in this research, which are 22 parameters, consisting of fifteen fuzzy parameters and seven nonfuzzy parameters. This paper also implements MFL to calculate all 22 parameters with the expert judgment weight, making the funding calculation better. Implementing MFL also makes the calculation more detailed by providing the calculation result from every category.

5 Conclusion

This research successfully fills the gap from previous research that can only produce a suggestion for one decision maker, either PVC or GVC. The GDSM created in this model can produce the suggested funding amount using SMM and MFL to examine twenty-two parameters with GVC and PVC expert judgment. The output from the model can help decision-makers, especially in GVC and PVC, to make more objective decisions in funding or investment. Another improvement can be made in the future, such as adding more parameters by doing literature reviews or interviews and adding more judgment from another investor perspective, such as banks or angel investors.

References

[1] O. Spiegel, P. Abbassi, M. P. Zylka, D. Schlagwein, K. Fischbach, and D. Schoder, "Business Model Development, Founders' Social Capital and The Success of Early Stage Internet Start-Ups: A Mixed-Method Study," *Information Systems Journal*, vol. 26, no. 5, pp. 421–449, Sep. 2016, doi: 10.1111/isj.12073.

[2] R. F. Bortolini, M. Nogueira Cortimiglia, A. de M. F. Danilevicz, and A. Ghezzi, "Lean Startup: A Comprehensive Historical Review," *Management Decision*, vol. 59, no. 8, pp. 1765–1783, 2018, doi: 10.1108/MD-07-2017-0663.

[3] I. R. Bednár and I. N. Tarišková, "Indicators of Startup Failure," *INTERNATIONAL SCIENTIFIC JOURNAL "INDUSTRY 4.0,"* no. 5, pp. 238–240, 2017, [Online]. Available: http://www.eban.org/about-angel-investment/early-stage-investing-

[4] C. Triebel, C. Schikora, R. Graske, and S. Sopper, "Failure in Startup Companies: Why Failure Is a Part of Founding," 2018, pp. 121–140. doi: 10.1007/978-3-319-72757-8_9.

[5] N. M. P. Bocken, "Sustainable Venture Capital - Catalyst for Sustainable Startup Success?," *J Clean Prod*, vol. 108, pp. 647–658, Dec. 2015, doi: 10.1016/j.jclepro.2015.05.079.

[6] E. Afful-Dadzie and A. Afful-Dadzie, "A Decision Making Model for Selecting Startup Businesses in a Government Venture Capital Scheme," *Management Decision*, vol. 54, no. 3, pp. 714–734, Apr. 2016, doi: 10.1108/MD-06-2015-0226.

[7] L. Grilli and S. Murtinu, "Government, Venture Capital and The Growth of European High-Tech Entrepreneurial Firms," *Res Policy*, vol. 43, no. 9, pp. 1523–1543, 2014, doi: 10.1016/j.respol.2014.04.002.

[8] B. S. Ardika, A. H. Setianingrum, and N. Hakiem, "Funding Eligibility Decision Support System Using Fuzzy Logic Tsukamoto (Case: BMT XYZ)," *Conference: 2017 Second International Conference on Informatics and Computing (ICIC)*, pp. 1--7, 2017.

[9] X. Tian, Z. Xu, J. Gu, and E. Herrera-Viedma, "How To Select a Promising Enterprise for Venture Capitalists with Prospect Theory Under Intuitionistic Fuzzy Circumstance?," *Applied Soft Computing Journal*, vol. 67, pp. 756–763, Jun. 2018, doi: 10.1016/j.asoc.2017.04.027.

[10] X. Liu, Z. Wang, S. Zhang, and J. Liu, "Probabilistic Hesitant Fuzzy Multiple Attribute Decision-Making Based on Regret Theory for The Evaluation of Venture Capital Projects," *Economic Research-Ekonomska Istrazivanja* , vol. 33, no. 1, pp. 672–697, Jan. 2020, doi: 10.1080/1331677X.2019.1697327.

[11] D. N. Utama, *Logika Fuzzy Untuk Model Penunjang Keputusan*, First. Yogyakarta: Garudhawaca, 2021.

[12] D. N. Utama, *Sistem Penunjang Keputusan: Filosofi, Teori dan Implementasi*, First. Yogyakarta: Garudhawaca, 2017.

[13] S. Kautish and M. P. Thapliyal, "Concept of Decision Support Systems in Relation with Knowledge Management – Fundamentals, Theories, Frameworks and Practices," *International Journal of Application or Innovation in Engineering & Management (IJAIEM)*, vol. 1, no. 2, pp. 1–9, 2012.

[14] D. J. Power, *Decision Support Systems: Concepts and Resources for Managers*. London: Quorum Books, 2002. [Online]. Available: https://scholarworks.uni.edu/facbook/67

[15] R. Rupnik, M. Kukar, P. Vračar, D. Košir, D. Pevec, and Z. Bosnić, "AgroDSS: A Decision Support System for Agriculture and Farming," *Comput Electron Agric*, vol. 161, pp. 260–271, Jun. 2019, doi: 10.1016/j.compag.2018.04.001.

[16] B. Alavi, M. Tavana, and H. Mina, "A Dynamic Decision Support System for Sustainable Supplier Selection in Circular Economy," *Sustain Prod Consum*, vol. 27, pp. 905–920, Jul. 2021, doi: 10.1016/j.spc.2021.02.015.

[17] C. Puchongkawarin and K. Ransikarbum, "An Integrative Decision Support System for Improving Tourism Logistics and Public Transportation in Thailand," *Tourism Planning and Development*, vol. 18, no. 6, pp. 614–629, 2021, doi: 10.1080/21568316.2020.1837229.

[18] D. N. Utama and G. Ramadhan, "Decision Support Model for Purchasing Decision in Pharmaceutical Company," *Article in Journal of Theoretical and Applied Information Technology*, vol. 15, p. 19, 2022, [Online]. Available: www.jatit.org

[19] L. Aggarwal, P. Goswami, and S. Sachdeva, "Multi-criterion Intelligent Decision Support system for COVID-19," *Appl Soft Comput*, vol. 101, Mar. 2021, doi: 10.1016/j.asoc.2020.107056.

[20] A. Asemi, A. Safari, and A. Asemi Zavareh, "The Role of Management Information System (MIS) and Decision Support System (DSS) for Manager's Decision Making Process," *International Journal of Business and Management*, vol. 6, no. 7, Jun. 2011, doi: 10.5539/ijbm.v6n7p164.

[21] M. Rabiee, B. Aslani, and J. Rezaei, "A Decision Support System for Detecting and Handling Biased Decision-Makers in Multi Criteria Group Decision-Making Problems," *Expert Syst Appl*, vol. 171, Jun. 2021, doi: 10.1016/j.eswa.2021.114597.

[22] M. Xia and J. Chen, "Multi-Criteria Group Decision Making Based on Bilateral Agreements," *Eur J Oper Res*, vol. 240, no. 3, pp. 756–764, Feb. 2015, doi: 10.1016/j.ejor.2014.07.035.

[23] K. Mittal, A. Jain, K. S. Vaisla, O. Castillo, and J. Kacprzyk, "A Comprehensive Review on Type 2 Fuzzy Logic Applications: Past, Present and Future," *Eng Appl Artif Intell*, vol. 95, Oct. 2020, doi: 10.1016/j.engappai.2020.103916.

[24] M. Mohsin, J. Zhang, R. Saidur, H. Sun, and S. M. Sait, "Economic Assessment and Ranking of Wind Power Potential using Fuzzy-TOPSIS Approach," *Environmental Science and Pollution Research*, vol. 26, no. 22, pp. 22494–22511, Aug. 2019, doi: 10.1007/s11356-019-05564-6.

[25] H. J. Mohammed, "The Optimal Project Selection in Portfolio Management using Fuzzy Multi-Criteria Decision-Making Methodology," *Journal of Sustainable Finance and Investment*, 2021, doi: 10.1080/20430795.2021.1886551.

[26] G. I. Perdana, M. D. Devanda, and D. N. Utama, "Fuzzy Based Butterfly Life Cycle Algorithm for Measuring Company's Growth Performance," *Journal of Advances in Information Technology*, vol. 14, no. 1, pp. 1–6, Feb. 2023, doi: 10.12720/jait.14.1.1-6.

[27] M. Amer and N. Elayoty, "Roadmap to Project Management Office (PMO) and Automation using a Multistage Fuzzy Rules System," 2018. [Online]. Available: www.ijacsa.thesai.org

[28] G. Büyüközkan and G. Tüfekçi, "A Multistage Fuzzy Decision-Making Framework to Evaluate The Appropriate Wastewater Treatment System: A Case Study," *Environmental Science and Pollution Research*, vol. 28, no. 38, pp. 53507–53519, Oct. 2021, doi: 10.1007/s11356-021-14116-w.

[29] A. F. Attia, A. Sharaf, and R. el Sehiemy, "Multi-Stage Fuzzy Based Flexible Controller for Effective Voltage Stabilization in Power Systems," *ISA Trans*, vol. 120, pp. 190–204, Jan. 2022, doi: 10.1016/j.isatra.2021.03.004.

[30] D. N. Utama *et al.*, "A Simple Performance Evaluation Model based on Multistage Fuzzy Slope," in *The 7th Engineering Science and Technology International Conference*, Dec. 2022, pp. 1–6. [Online]. Available: https://www.researchgate.net/publication/366963817

[31] J. Merelä, "Optimizing Value for Funding Rounds: Funding Strategy for Startups," 2020.

[32] E. Engberg, P. G. Tingvall, and D. Halvarsson, “Direct and Indirect Effects of Private and Government-Sponsored Venture Capital,” *Empir Econ*, vol. 60, no. 2, pp. 701–735, Feb. 2021, doi: 10.1007/s00181-019-01770-w.

[33] H. Liao and X. Wu, “DNMA: A Double Normalization-Based Multiple Aggregation Method for Multi-Expert Multi-Criteria Decision Making,” *Omega (United Kingdom)*, vol. 94, Jul. 2020, doi: 10.1016/j.omega.2019.04.001.

[34] G. O. Odu, “Weighting Methods for Multi-Criteria Decision Making Technique,” *Journal of Applied Sciences and Environmental Management*, vol. 23, no. 8, p. 1449, Sep. 2019, doi: 10.4314/jasem.v23i8.7.

[35] D. Singh and B. Singh, “Investigating the Impact of Data Normalization on Classification Performance,” *Appl Soft Comput*, vol. 97, Dec. 2020, doi: 10.1016/j.asoc.2019.105524.

[36] W. Mohd and L. Abdullah, “Aggregation Methods in Group Decision Making: A Decade Survey,” *Informatica*, vol. 41, pp. 71–86, 2017.